The Report committee for Ross Ardley Buchanan Certifies that this is the approved version of the following report:

Responsiveness and Feedback under Authoritarianism:

The Public, City Governments, and Air Pollution in China

Committee:

____
Bryan Jones, Supervisor

____
Xiaobo Lu

Responsiveness and Feedback under Authoritarianism:

The Public, City Governments, and Air Pollution in China

by

Ross Ardley Buchanan

Report

Presented to the Faculty of the Graduate School of

the University of Texas at Austin

in Partial Fulfillment

of the Requirements for the Degree of

Master of Arts

The University of Texas at Austin

August 2018

Acknowledgments

This report was done with the help of Lingna Zhong, who is currently an assistant professor at Central China Normal University. She was instrumental in obtaining the economic data for Chinese cities and the government reports. I also consulted with her regularly while creating the theoretical model presented in this paper.

Responsiveness and Feedback under Authoritarianism:

The Public, City Governments, and Air Pollution in China

by

Ross Ardley Buchanan, MA

The University of Texas at Austin, 2018

Supervisor: Bryan Jones

Recent scholarship on authoritarian responsiveness has found limited, ad hoc responsiveness to public concern by local governments in China. However, almost nothing is known about the outcomes of this responsiveness. We do not know if the outcomes are ever substantively meaningful for the public, nor whether they "feed back" on public concern in authoritarian systems. To address this gap, I propose a novel responsiveness-feedback model with outcomes, and apply it to air pollution in Chinese cities because of the issue's importance and objectively measurable severity. I estimate the relationships between pubic concern, government action, and air pollution levels in 273 cities from 2013-2015 using structural equation models to account for feedback, and find evidence of substantively meaningful responsiveness and outcomes-based feedback. I speculate that our model also applies to other topic areas that can be addressed by local governments and have outcomes the public can directly observe.

TABLE OF CONTENTS

1 INTRODUCTION

The degree to which a government responds to public concern is an important issue in political science. Every person's wellbeing depends in part on the degree to which his or her government responds to citizens' concerns. While responsiveness in wealthy democracies has been well studied (Jennings 2009; Jones et al. 1977; Mladenka 1981; Soroka and Wlezien 2010; Wlezien 1995) responsiveness in authoritarian systems remains poorly understood. Recent studies on China have found limited, ad hoc responsiveness in issue areas the regime considers non-sensitive (Cai 2010; Distelhorst and Hou 2017; Manion 2014; Meng, Pan, and Yang 2017; Truex 2016). However, little is known about the substantive outcomes. We do not know if the ad hoc responsiveness scholars have identified ever aggregates into outcomes that are meaningful for the general public—or whether the responsiveness is too infrequent, narrowly targeted, and superficial to be perceptible. We also do not know whether the outcomes themselves influence public concerns through a "feedback" effect.

This paper proposes a model of policy responsiveness and feedback at the local level in an authoritarian system. For responsiveness, we theorize that 1) public concern with a problem increases the level of local government action addressing that problem, and 2) the increased government action mitigates the problem's severity. For feedback, we theorize that a problem's severity has a direct, positive feedback effect on 1) public concern, and 2) government action directed at the problem (see Figure 1 in the theory section). To empirically test this model, we look at a specific policy domain in an authoritarian system: air pollution in Chinese cities. We look specifically at this issue because it is universally important, observable by the public, and objectively measurable.

Testing this model requires estimating the relationships between public concern, government action, and air pollution. To do this, we use a structural equation model (SEM), which allows us to account for the error correlation that often results from feedback dynamics. I compare the SEM results with standard regressions that assume uncorrelated errors, and conduct a series of robustness checks that account for air pollution spillover between cities. The analysis is based on a sample of 273 Chinese cities from 2013-2015.

The empirical results support the model, allowing this paper to make two major contributions. The first is finding evidence of substantively meaningful responsiveness in an authoritarian system. The implication of this finding is that the limited, ad hoc responsiveness extant scholarship has found in China appears to aggregate into outcomes large enough to significantly affect the general public within this issue domain. Until now, there has been no clear evidence that substantive responsiveness exists within *any* issue domain in China or other authoritarian regimes. Thus, this finding is itself an important contribution. It is also an important step towards understanding how responsiveness varies across issue areas in non-democratic settings.

The second contribution is finding evidence of a feedback dynamic in an authoritarian system. Feedback has been studied in wealthy democracies, most notably by scholarship on the thermostatic model (Jennings 2009; Soroka and Wlezien 2010; Wlezien 1995).[1] However, there are no studies that examine this phenomenon in an authoritarian context. A notable characteristic of the feedback I find is that it is driven by an outcome (i.e., air pollution). This contradicts the thermostatic model which predicts only policy-based feedback, where the public responds directly to the policies addressing an issue and not outcomes of those policies (Soroka and Wlezien 2010; Wlezien 1995). The outcomes-based feedback we find may have implications for our understanding of responsiveness and feedback dynamics beyond the authoritarian context. For reasons we touch on in the final section, I speculate that outcomes-based feedback tends to dominate at the local level where outcomes are more concrete and easily observable, while policy-based feedback dominates at the national level.   Whatever the cause of this contradiction turns out to be, our finding suggests a fruitful path for future scholarship.

While this study looks only at air pollution in Chinese cities, this model may also apply to other countries and issue areas. As a highly authoritarian regime, China is likely not drastically more responsive to public concern than other countries with strong states, be they democracies or dictatorships. It is therefore plausible that our model applies to other countries with air pollution problems. This model may apply to other issue areas too, as its logic is consistent with any domain where local actors have influence and the public can directly observe outcomes. Such issue areas may include public transportation, road maintenance, and other forms of local infrastructure.

[1] The model stipulates that public preferences for more (less) government spending in an issue area causes the government to respond, and that the government responding to those preferences reduces the public's preference for additional spending increases (decreases) in that issue area.

2 STATE OF THE LITERATURE

The primary driver of authoritarian responsiveness in China is self-preservation, both at the level of the regime and individual officials. Avoiding—and, when necessary, containing—outbreaks of public upheaval is necessary for the regime's survival. For individual officials, the maintenance of social stability is one of the few firm criteria for career advancement within the regime. Public protests and other visible indicators of social instability threaten the career prospects of officials at all levels of the political system (Göbel and Ong 2012).

2.1 AUTHORITARIAN RESPONSIVENESS: WHAT WE KNOW

Responsiveness in China is ad hoc. The strong incentives officials face to avoid (or quickly deescalate) protests lead them to monitor for and react to signs of upheaval. When faced with social unrest, officials typically respond with the easiest method available to contain the problem. Often, these methods are repression and stonewalling, as has been seen in such high-profile cases as the 2008 powdered milk crisis.[2] But in some instances, the easiest course of action is (partially) capitulating to citizens' demands. Government officials are most likely to be responsive to citizens in situations where the cost of repression is high relative to the cost of minimally conceding to the demands (Cai 2010; W. Li, Liu, and Li 2012; Mertha 2008).

Responsiveness is also driven by the *threat* of social unrest, as officials seek to preempt and prevent protests when possible. An example of this can be seen in a recent field experiment by Chen, Pan, and Xu (2016), which found that local officials were more likely to respond to citizens' pension payment requests when the requests included thinly veiled threats of collective action. More broadly, there is considerable circumstantial evidence that officials sometimes seek to avoid protests by preemptively addressing public concerns they view as likely to foment social instability (Manion 2014; Truex 2016). Indeed, China's extensive infrastructure for monitoring public sentiment likely exists to identify the public concerns most prone to fuel unrest (Brady and Juntao 2009).

Responsiveness varies by issue area. The regime is not responsive in domains it considers to pose existential threats to its survival. These sensitive domains are not precisely defined, but include issues such as censorship, free speech, and human rights. Outside these sensitive areas, ad hoc

[2] In the 2008 powdered milk crisis, melamine contamination of milk powder led to the hospitalization of tens of thousands of infants and multiple deaths. The local and national government ignored the complaints filed by irate parents, and imprisoned the parent Guo Li, who tried to obtain compensation from a milk manufacturer.

responsiveness has been observed across a wide range of issue areas, includes environmental degradation (W. Li, Liu, and Li 2012), housing demolition (Mertha 2008), and pension payments (Cai 2010; Chen, Pan, and Xu 2016).

2.2 Limitations

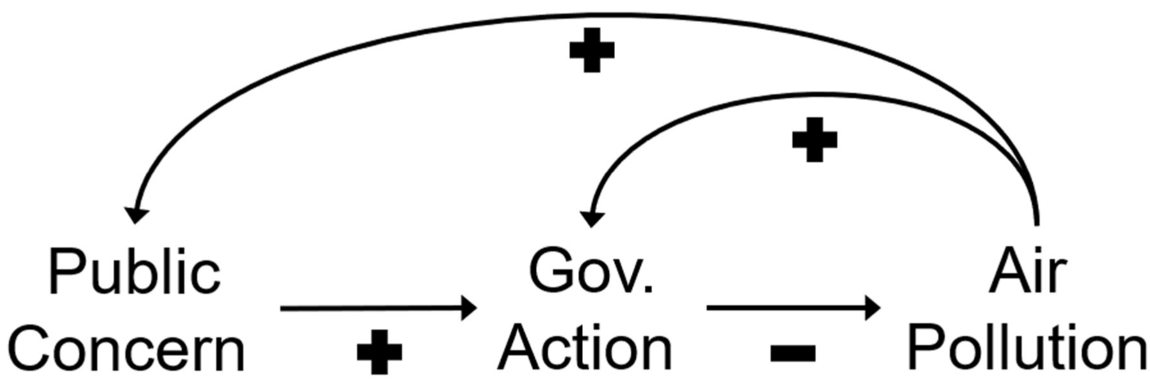
Without accounting for outcomes, we do not know whether and to what extent a regime's ad hoc responsiveness affects the general public. While we know that responsiveness does not exist in highly sensitive issue areas, extant scholarship has not established whether substantive responsiveness exists within any issue domain in China.

Ignoring outcomes and feedback has also undermined quantitative analysis on this subject. Statically estimating responsiveness generally involves regressing indicators of government action on public opinion. Indeed, positive relationships between the two have been found in China with this type of analysis (Tang, Chen, and Wu 2018). While such relationships are consistent with substantive responsiveness, inferring causality is deeply problematic when outcomes and feedback are not accounted for. If both public opinion and government action are driven by an outcome like air pollution severity, they will correlate even if no causal relationship exists. As for feedback, ignoring it risks biased estimates, as feedback may cause variables' errors to correlate.

3 THEORY

This paper's theoretical model of responsiveness and feedback pertains to air pollution at the city level in China. It consists of three variables—public concern, government action, and air pollution—and four causal relationships (see Figure 1). Two of the relationships are aspects of responsiveness while the other two are forms of feedback. For responsiveness: 1) public concern has a positive effect on government action and 2) government action has a negative effect on air pollution. In other words, more (less) public concern increases (decreases) government action, and more (less) government action decreases (increases) air pollution. For feedback: 3) air pollution has positive effects on both public concern and 4) government action. That is, more (less) air pollution increases (decreases) public concern and government action. These variables pertain to the publics, governments, and pollution levels of cities.

Figure 1: Theoretical Model. The plus (+) and minus (—) signs signify theorized positive and negative causal relationships respectively.



These theoretical relationships can be formally expressed as a system of equations, where P is the concern of the public in city i over local air pollution at time t, G is the total action of the city government to mitigate local air pollution levels, A is the local air pollution level, ΔA is change in air pollution, and Z_1, Z_2, and Z_3 are vectors of control variables that we discuss in appendices A, B, and C. In the remainder of this section, we define each of these variables and explain the relationships we theorize between them.

$$P_{i,t} = f\left(A_{i,t}, \Delta A_{i,t}, \boldsymbol{Z_{1,i,t}}\right) \tag{1}$$

$$G_{i,t} = g\left(P_{i,t-1}, A_{i,t-1}, \Delta A_{i,t}, \boldsymbol{Z_{2,i,t}}\right) \tag{2}$$

$$A_{i,t} = h\left(G_{i,t}, \boldsymbol{Z_{3,i,t}}\right) \tag{3}$$

3.1 Public Concern

1.1.1 What Is Public Concern?

Public concern refers to the intensity of the public's preference for the local government to take more action on air pollution. The term combines pollution's salience with the assumption that the public prefers more government action to address the issue. This concept rests on two premises: 1) citizens viewing air pollution as salient entails a preference for the government to do more about it, and 2) the salience level corresponds to the public's prioritization of the issue. We know empirically that the direction of the public's preference does not vary meaningfully with salience in this issue area; even when air pollution's salience is low, overwhelming majorities of citizens prefer more government action to address the problem (Lo and Leung 2000, 688). Rather, what changes with salience is the public's prioritization of the problem. When air pollution's salience is low, the public sees other problems as more pressing and worthy of government attention (Lo and Leung 2000, 687), but as salience increases the public sees the problem as more urgent and in need of more of the government's attention (Fedorenko and Sun 2016).

Public concern is related to public demands for government action. Concerns are attitudes that citizens may choose to express or keep to themselves. Demands are articulated. While these concepts are not synonymous, they are closely associated. As public concern increases—in terms of the number of concerned people and the intensity of their concerns—the number and severity of the demands they articulate to government officials also increases. Concern with air pollution has been found to correspond with the volume of public demands directed at both the national and local governments in China (Y. Dong et al. 2011; Xianbing Liu et al. 2011).

3.1.1 Causes of Public Concern

Public concern with air pollution is a function of the pollution's severity, which has two aspects: the absolute level of air pollution, and the extent to which it is getting better or worse. If absolute air pollution levels (*A*) are low, citizens have less reason to be concerned with air pollution relative to other problems, and less reason to expend time and energy pressuring local officials to take action on that issue. High levels of air pollution, on the other hand, represent a serious problem that raises public concern and motivates citizens to intensify their demands that the local government do more to address it. Extant scholarship demonstrates this relationship. Chinese citizens submit more complaints about air pollution to all levels of government when concentrations are high (Y. Dong et al. 2011; Xianbing Liu et al. 2011).

The change in air pollution (ΔA) reflects the extent to which the problem is getting better or worse. If the problem is getting worse, the public has more reason to be concerned than when it is stable or improving. While the relationship between public opinion and the change in problem intensity has not been well studied in China or other authoritarian systems, it has been shown to exist elsewhere. Scholarship comparing public opinion and economic performance in the United States, for instance, has found that citizens are highly sensitive to the extent to which performance has gotten better or worse over the previous two years (Wlezien 2015).

How do citizens know A and ΔA? People can directly perceive air pollution's absolute level and change over time. Studies conducted in China and elsewhere have shown that self-reported annoyance with pollution is highly sensitive to how much is in the air, and that the public accurately perceives how air pollution levels have changed over the previous three years (Amundsen, Klaeboe, and Fyhri 2008; Klaeboe, Amundsen, and Fyhri 2008; Lo and Leung 2000).

3.2 Government Action

3.2.1 What Is Government Action

Government action refers to the aggregation of activities by local governments that mitigate air pollution output. It is, in effect, a very broad conception of public policy. We conceptualize government action as having two aspects. One is the pre-implementation stages of policymaking, which includes the local political leadership's search for policy solutions, deliberation, and the formation of official policies, goals, and priorities (Kingdon 1995). The other is a government's implementation efforts. This refers primarily to the activities of the leadership's subordinates—particularly street level bureaucrats and other low level officials—that affect local air pollution emissions. Recognizing these two aspects of government action is important because they may not always closely correspond. Policies can be created by political leaders but never meaningfully carried out, and subordinates can vary the amount of effort they put into mitigating air pollution without directives from the leadership.

The distinction between these two aspects of government action is especially relevant in this case because there is abundant evidence that the implementation of air pollution-related policy is far more sensitive to public concern than official policy is. Case studies, interviews with local environmental protection bureau (EPB) officials, and quantitative assessments have found that citizens' demands for more air pollution enforcement greatly increase the effort low level city officials put into mitigating air pollution (Lo and Leung 2000; Lo and Fryxell 2005; Van Rooij and Lo 2010; H. Wang 2000). Furthermore, in one of the few nation-wide studies on this subject in China, Zheng and Shi (2017) find that official environmental policies and public complaints have independent effects on polluting firms' decisions to leave a province. This pattern of disinvestment by polluting firms suggests that both official policy *and* public pressure have sizable impacts on how effectively air pollution emissions are regulated in practice. It also suggests that much of the public's effect on government implementation efforts is direct and not a byproduct of responsive official policy.

3.2.2 Causes of Government Action

Government action is a function of public concern (*P*). We theorize that the main mechanisms through which public concern affects government action are those identified by the responsiveness literature. Environmental degradation is a prominent driver of social unrest in China (Göbel and Ong 2012; W. Li, Liu, and Li 2012), and air pollution is one of several issues on which local governments receive high volumes of complaints (Warwick and Ortolano 2007). Local officials are therefore likely to use these complaints (and other tools at their disposal) to gauge public concern and work to mitigate air pollution to the degree necessary to stave off social unrest.

We also expect that public concern affects government action through more subtle, less coercive, mechanisms. Local Environmental Protection Bureau (EPB) officials have said in interviews and surveys that public support for environmental enforcement increases the effectiveness of their efforts

(Lo and Fryxell 2005; Zhan, Wing-Hung Lo, and Tang 2014). Along these lines, there is evidence that citizens can influence local governments' enforcement efforts by submitting complaints that help EPB officials to identify illegal polluting activities (Warwick and Ortolano 2007).

Government action is also a function of air pollution severity (*A* and *ΔA*). Despite Chinese officials' notoriously weak commitment to environmental protection (see Appendix B), we theorize that they respond directly to air pollution severity to some degree. Local officials have obvious incentives to head off problems form the public or upper levels of government, and qualitative work has shown that officials are well aware that severe air pollution can attract the ire of local citizens and their superiors (Lo and Fryxell 2005; Lo, Fryxell, and Wong 2006; Warwick and Ortolano 2007; Zhan, Wing-Hung Lo, and Tang 2014). In addition, officials and their families typically live in the cities where they work and breath, so they may be motivated in part by personal reasons. It is also possible that some feel a sense of professional responsibility to address a problem they see in front of them.

3.3 Air Pollution

Air pollution refers to the average concentration of air pollution at ground level within a city's boundaries. It is a function of local government action (*G*). When local governments do more to mitigate air pollution, air pollution will be lower than it would otherwise be. The opposite is also true. It is important to note that while air pollution is a function of government action, government action is *not* the primary determinant of a city's air pollution level—at least not in the short to medium term. The main driver of local air pollution is local economic output, which we discuss along with the other controls in Appendix C. Conceptually, one can think of government action as a force that pushes air pollution levels above or below a "natural level" that is determined by local economic output and the other control variables.

By what means does government action affect air pollution emissions? There are likely many mechanisms at work, as any action that reduces a city's automobile traffic, or reliance on coal for electricity, heating, or cooking would reduce pollution emissions to some degree. However, the mechanism over which the local governments have the most direct control is the use of various forms of regulatory enforcement to pressure polluting firms to relocate to other cities. City governments use this mechanism extensively. In a case study based on site visits and interviews with city EPB officials and senior firm managers in Shangyu, Zhu (2014) found that many local firms were relocating to other cities in China because of increasing environmental regulation enforcement by the local government. Large-n studies have corroborated Zhu et al.'s finding that environmental enforcement by local governments is a major factor causing polluting firms to relocate. Zhou et al. (2017) and Zheng and Shi (2017) find that pollution intensive industries are more likely to leave cities which claim to strictly enforce air pollution regulations and are more likely to enter cities that do not. Wu et al. (2017) conduct a similar study of water pollution regulation at the province level and reach the same conclusion. Zhang et al. (2008) find that foreign direct investment for polluting industries tends to gravitate towards areas that report having looser anti-pollution enforcement.

4 DATA

4.1 PUBLIC CONCERN

Our measure of public concern is the Baidu index of Internet searches related to air pollution.[3] The index represents the annual number of air pollution-related searches relative to the total search volume in each city going back to 2011. It is functionally identical to Google's search index (Vaughan and Chen 2015). Fundamentally, a search index reflects an issue's salience (Mellon 2013); it does not necessarily indicate the public's preferences for government action on a given issue. However, as discussed earlier, air pollution's salience corresponds with the intensity of the public's preference for the government to do more to mitigate the problem (Fedorenko and Sun 2016; Lo and Leung 2000). Indeed, Internet search indices have been found to be a reliable indicators of public preferences for government action on environmental issues cross-nationally (Oehl, Schaffer, and Bernauer 2017).

Government censorship of the Internet is pervasive in China but unlikely to bias this measure. The specific topics targeted by China's online censors are constantly shifting and notoriously difficult to track. Nevertheless, we expect that most censorship related to air pollution takes the form of blocked websites as opposed to blocked search terms, meaning that people's pollution-related searches should be reflected in the search index regardless of which websites are easily accessible. To whatever extent blocked search terms do bias the measure, the likely result would be to under-represent increases in public concern, for censorship of a topic would presumably be most pervasive in the face of swelling public attention. Thus, even if censorship biases the measure, the result would be to make the key statistical relationships in our analysis *less* significant.

The one caveat to the search index measure is that it is not perfectly representative of the entire population. China's Internet penetration was roughly 34 percent in 2011 and 48 percent in 2015, and Internet users are disproportionately well educated, non-poor, and urban (China Internet Network Information Center 2011, 2015). Even so, we expect that the search index is a decent indication of the entire public's concern, as concern levels among societal groups in the same area are likely to move together in an issue area that affects the entire population. To the extent the search index is not representative of the entire public, it reflects the concerns of the 34 or 48 percent of the population that government officials are most likely to be responsive to. Compared to the average citizen, those who

[3] Baidu is the dominant Internet search engine in China.

are educated, non-poor, and urban tend to be more concerned with air pollution (Yu 2014), more prone to complaining to government officials (Y. Dong et al. 2011; Xianbing Liu et al. 2011), and more willing to undertake collective action (J. Liu 2011).

4.2 Government Action

Our government action measure is derived from city governments' work reports. Work reports are published by nearly all city governments (as well as the other levels of China's state) within the first two months of each year. The first section of the reports highlights the governments' accomplishments over the previous year, while all subsequent sections lay out their broad goals for the new year.[4] The measure is the proportion of each report's prospective section that discusses topics directly related to air pollution. To calculate this proportion, we identify all paragraphs that include one or more keywords[5] and then divide the combined length of those paragraphs by the length of the report's entire prospective section.[6]

The reports are a *partial* indicator of government action. They are indicative of the local leadership's policy priorities, which reflect one aspect of government action. As Z. Wang (2017) finds in a recent qualitative study, governments put substantial effort into writing the reports and following through with their stated goals. However, the reports are not a *comprehensive* indicator of government action, for they are unlikely to reflect other factors that directly influence implementation efforts. As noted earlier, extant scholarship suggests that much of the public's impact on government action is directly on low level officials' implementation efforts and not through responsive official policy (Lo and Leung 2000; Lo and Fryxell 2005; Van Rooij and Lo 2010; Zhan, Wing-Hung Lo, and Tang 2014; Zheng and Shi 2017).

[4] At the start of a new five year plan, section two focuses exclusively on five year goals while subsequent sections discuss goals for the year. We exclude the section twos from our analysis in these cases.
[5] For the list of keywords, see Appendix I.
[6] We measure paragraph and section length by the number of characters because of the technical difficulty of performing accurate word counts in Chinese. Chinese words are generally not separated by spaces or other unique markers.

4.3 Air Pollution

We measure air pollution using satellite-derived tropospheric (i.e., the air at ground level) nitrogen dioxide (NO_2) concentrations.[7] NO_2 is well suited for this study because it is both a dangerous air pollutant and an indicator of overall air pollution levels. Exposure to NO_2, which is a major component of smog, causes immediate physical discomfort and is associated with serious long term health problems, including respiratory disease and dementia (Amundsen, Klaeboe, and Fyhri 2008; H. Li and Xin 2013). NO_2 levels are also indicative of a city's overall air pollution level, for it is generated by the same economic activities as other major pollutants (Fontes et al. 2017). Its primary emissions sources are combustion processes, such as those in automobile engines, coal fire power plants, and heavy industry (Chan and Yao 2008). NO_2 is also preferable to other common pollutants because it has a relatively short lifespan and is thus a more accurate indicator of *local* emissions (see Appendix C).

Using satellite data allows us to avoid biased measurements from China's ground sensors. Local officials have strong incentives to manipulate pollution data and the sensors themselves, and the country's pollution data show extensive evidence of tampering (Ghanem and Zhang 2014). Any measurement error in the satellite data should be effectively random and not introduce bias.

[7] We use the European Space Agency's DOMINO dataset (version 2), which is derived from the daily overpass measurements of the OMI sensor on the AURA satellite using the KNMI atmospheric model. We discuss how we upscale the resolution of the data and compensate for imperfect spatial coverage in Appendix L.

5 CONTROLS

When air pollution is the outcome, local economic output is the most important control. As discussed in Appendix C, local economic output is the main determinant of municipal air pollution because local economic activities are the primary emissions sources. Our measure for each city's economic output (i.e., gross regional product—GRP) is derived from the data reported in China's official Statistical Yearbook. The Yearbook values are nominal, so to account for regional purchasing power variation, we use the estimates of Brandt and Holz (2006) for price differences between provinces. We then use the official consumer price index of each province to convert all totals into renminbi for the year 2000 to account for inflation.

China's reported economic indicators are famously suspect and there is abundant anecdotal evidence that official economic output measures are greatly inflated. Even so, we are confident that official GRP statistics are valid measures for our purposes because this study depends on accurate measurement of *change* in GRP from one year to the next. Satellite images of changes in China's nighttime brightness, which correspond to changes in economic output (Henderson, Storeygard, and Weil 2012), imply that China's reported output statistics are either not greatly inflated or (more likely) inflated consistently over time (Landry, Lü, and Duan 2018). To whatever extent GRP values are not inflated consistently, the error terms in our models will increase, but we see no reason to think that the additional error would bias our results.

We also control for pollution spillover between cities. There is no optimal method for dealing with this issue, so we use four different approaches. Each approach is imperfect, but consistency between them makes it unlikely that spillover is biasing our results. The first method is to do nothing. Ground level NO_2's spillover tends to be low compared to other pollutants, and may be small enough that we can simply ignore it (see Appendix C). The second is to use the mean NO_2 level of each city's eight closest neighbors as a control variable. This approach treats pollution spillover as exogenous—it accounts for pollution being blown in from a city's surroundings, but does not account for autocorrelation between neighboring observations in our analysis. The third approach is to cluster the standard errors of our observations by province. This approach helps account for autocorrelation between observations within the same provinces, but not between observations in different provinces.[8]

[8] We only include the first two methods in Table D1. For all three methods, see Table E1.

The fourth method is to use a lagged spatial autoregression (SAR) model, which explicitly accounts for autoregression among city's NO_2 level and those of its neighbors. This is the most attractive approach in principle, but it comes with two limitations. The most serious of these is that incorporating an SAR into an SEM is currently impractical. The SAR model therefore cannot account for the endogeneity we theorize. The second is that we lack specific theoretical expectations for how each city's neighborhood should be defined. Monte Carlo simulations suggest that specific neighborhood definitions tend not to have a meaningful effect on model estimation so long as the models are correctly specified (Fotheringham and Oshan 2016), but this issue has been contentious among geographers (Gibbons and Overman 2012). We therefore try a variety of different neighborhood definitions to determine that the results are consistent (see Appendix F).

To control for top down pressure from the national government to mitigate air pollution we use the national government work reports. The measure is derived with the same method used for the city work reports. We also use a measure of per capita GRP to help account for miscellaneous factors that may influence our results, such as a city's overall level of economic development and the financial resources at a government's disposal. The per capita GRP values of each city are taken from the Statistical Yearbook and adjusted for inflation and regional purchasing power variation the same way the absolute GRP values are.

To help account for the unmeasured variables discussed in the appendices A, B, and C, we use two approaches. The first is to include province fixed effects. The second is to incorporate lagged dependent variables in our models, which control for unmeasured, city-specific factors that do not vary meaningfully from one year to the next.[9]

[9] We also show that our results are robust to the inclusion of year fixed effects (Appendix M) and province random effects (Appendix N).

6 Model Specifications

The three equations in our SEM are as follows. The alphas are the intercepts, the betas are the coefficient estimates, the *e*'s are the error terms, and the gamma hats are the estimates for the vectors of control variables. *i* and *t* represent the city and year of each observation.

$$Search.Index_{i,t-1} = \alpha_{1,0} + \beta_{1,1}NO2_{i,t-1} + \beta_{1,2}\Delta NO2_{i,t-1} + \widehat{\gamma_1} + e_{1,i,t-1} \tag{4}$$

$$Reports_{i,t} = \alpha_{2,0} + \beta_{2,1}NO2_{i,t-1} + \beta_{2,2}\Delta NO2_{i,t-1} + \beta_{2,3}Search.Index_{i,t-1} + \widehat{\gamma_2} + e_{2,i,t} \tag{5}$$

$$NO2_{i,t} = \alpha_{3,0} + \beta_{3,1}Reports_{i,t} + \beta_{3,2}Search.Index_{i,t-1} + \widehat{\gamma_3} + e_{3,i,t} \tag{6}$$

7 ANALYSIS

Figures 2 and 3 show our theoretical expectations for each relationship in the SEM and the results for the fully specified model, which correspond to Model 2 in Table 1. We use this figure for the sake of clarity, as the SEM includes multiple relationships of interest.[10]

Figure 2: Theoretical expectations. Solid arrows indicate the theorized causal direction between variables. The dashed gray arrows indicate relationships for which we have no theoretical expectations but include for exploratory purposes. The plus (+) and minus (—) signs indicate expected positive and negative relationships respectively. The arrows originating from NO_2, indicate its theorized relationship with the other two variables in the next time period: the search index for year t and the reports for year t + 1.

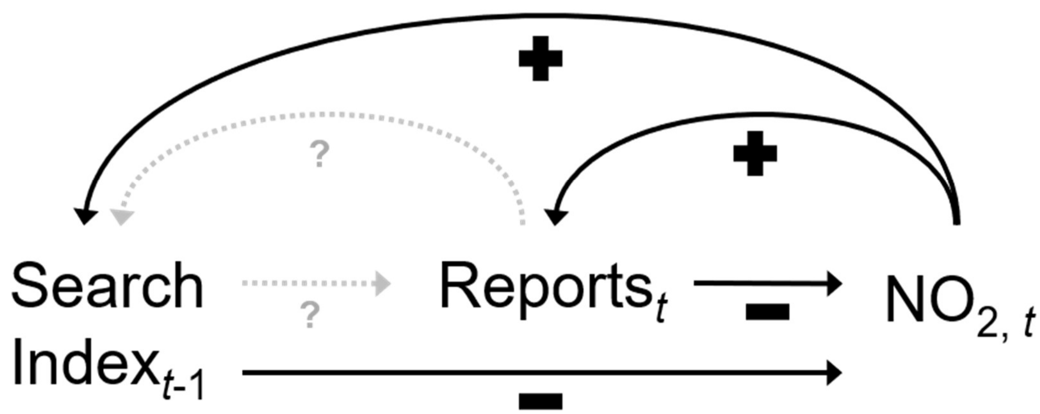
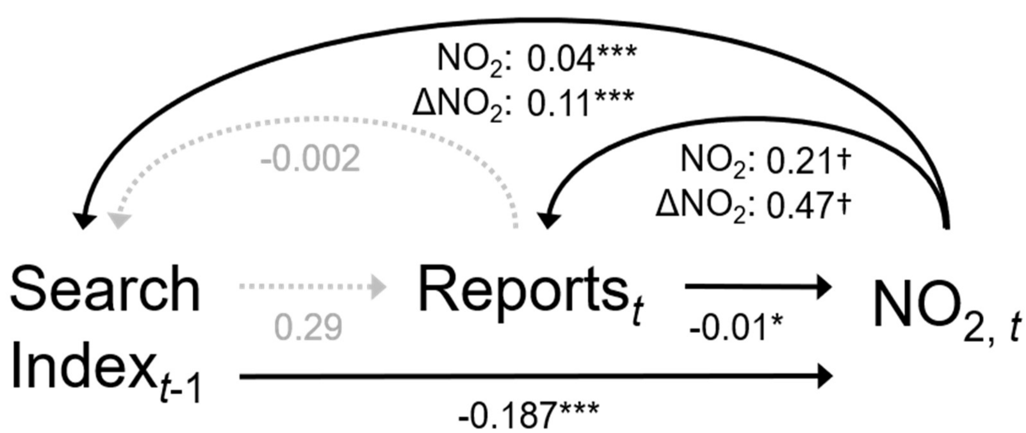


*Figure 3: Empirical results. The values are the coefficients for Model 2 in Table 1. †p<0.1; *p<0.05; **p<0.01; ***p<0.001. N = 727.*



[10] The following analysis includes all observations for which data is available (see Appendix J).

The relationship most directly relevant to responsiveness is the search index's effect on NO_2, as it represents public concern's effect on local air pollution. We expect the search index to have a direct negative effect on NO_2 in the following year. Why do we expect a *direct* effect? After all, we theorize that public concern affects air pollution through responsive government action. As discussed earlier, however, the reports are unlikely to reflect much of the influence public concern has on implementation efforts, which is where existing scholarship has found public concern to have the greatest influence on government action (Lo and Leung 2000; Lo and Fryxell 2005; Van Rooij and Lo 2010; Zheng and Shi 2017). Thus, we theorize that the search index's "direct" effect on NO_2 represents the government action that is caused by public concern and not reflected by the reports measure.

For the feedback between outcomes and public concern, we expect a city's NO_2 to have a positive effect on the search index of the same year. Local NO_2 levels should affect the search index almost instantly because citizens directly perceive NO_2 and Internet searches are low cost and require no advanced planning. We expect NO_2 levels relative to the previous year (ΔNO_2) to have a positive effect on the search index as well. More (less) severe air pollution should cause more (less) public concern.

The reports are expected to have a negative effect on NO_2. The reports reflect the government leadership's priorities, so more attention to air pollution in the reports should represent an increase in governments' mitigation efforts and lead to lower NO_2 levels. Because the reports are released at the beginning of each year and contain annual goals, they should affect NO_2 over the course of that year. NO_2's effect on the following year's reports represents the extent to which governments are responding directly to air pollution. We expect this relationship to be positive, but relatively weak given local officials' generally anemic commitment to environmental protection (Eaton and Kostka 2014).

For the relationships between the search index and the reports, we have no specific theoretical expectations. While extant scholarship leads us to believe that most of public concern's effect on government action is not reflected in the reports, it is not clear whether the reports are still sensitive to public concern to some extent. For the reports' effect on public concern, we also have no expectations. Our theory that outcomes feed back on public concern does not preclude the possibility that government action feeds back as well.

As shown in Figure 3, each relationship corresponds with our theoretical expectations, and the evidence for substantive responsiveness becomes more persuasive when the results are looked at as a whole. The search index's estimated effect on pollution levels the following year is consistent with the substantive responsiveness we theorize. If unobserved forms of government action are responding to public concern, a robust negative effect of the search index on NO_2 is what we should see. However, this statistical relationship is also consistent with a plausible alternative explanation: government action may be responsive to the air pollution problem itself, and not public concern. In this alternative scenario, public concern and government action would correlate because they would be responding to the same signal, and—assuming the government action was effective—the search index would be negatively associated with NO_2 the following year despite the absence of a causal link.

The pair of relationships between the reports and NO_2 help to discount this alternative explanation. These relationships suggest that government action is indeed driven in part by air pollution severity itself; NO_2 and ΔNO_2 have positive estimated effects on the reports, and the reports have a negative estimated effect on local NO_2.[11] However, if government action were responding *only* to air pollution, the reports' effect on NO_2 should wipe out—or at least greatly reduce—the search index's effect.[12] What we actually see is that the search index remains highly significant even with the reports measure in NO_2's equation. Moreover, the inclusion of reports as an explanatory variable for NO_2 has only a negligible impact on the search index's estimated effect.[13]

It is of course impossible to definitively prove there are no other factors causing a spurious relationship between the search index and NO_2 the following year, but the possibility is remote. We are aware of no other plausible alternative explanations for this relationship. Furthermore, our model explains 96 to 97 percent of NO_2's variation and 82 percent of the search index's variation.[14] Such high R^2 values imply that there are no important missing variables that could potentially bias our results and cause spurious correlation.

[11] A one standard deviation increase of the reports measure is estimated to cause a 7 $\mu g/m^3$ reduction in NO_2, which represents a decrease of a little over 1 percent for the average observation.
[12] Are the policy implementation efforts of low level functionaries responding directly to air pollution severity? If there is an effect, it is very small. Interviews and surveys of local EPB officials aimed specifically at identifying the factors that influence their implementation efforts have not found air pollution severity to be a significant factor, while they have found public concern to have a major effect (Lo and Fryxell 2005; Lo, Fryxell, and Wong 2006; Zhan, Wing-Hung Lo, and Tang 2014).
[13] See Appendix G for the results of models without the reports' effect on NO_2.
[14] We suspect much of the search index's remaining unexplained variation is due to random fluctuations in the salience of other issues on the public's agenda (see Appendix A).

The results are also supportive of the feedback dynamic we theorize; NO_2 and ΔNO_2 have positive, highly significant estimated effects on the search index. Interestingly, the feedback effect appears to be entirely outcomes-based. Our findings imply that public concern is directly affected by air pollution severity and not at all by government action.[15] This finding contradicts the policy-based feedback predicted by the thermostatic model. As we discuss in the next section, we speculate that we find outcomes-based feedback because this study examines local-level politics, where citizens can directly observe the outcome.

So far, we have only discussed the results for the fully specified SEM. This model includes a spillover variable and assumes that the search index's and NO_2's errors are correlated due to the ongoing feedback dynamic we theorize. However, it is informative to compare these results with results for models that ignore feedback. Unmeasured factors that affect NO_2 levels and persist over time—an economic boom in an upwind region, for instance—will tend to push both NO_2 and the search index in the same direction if, as we theorize, NO_2 levels have a positive effect on the search index.[16] The estimated effect of the search index on NO_2 is therefore likely to be biased in the positive direction if feedback is present. Because we theorize the search index has a negative effect on NO_2, the bias should make the magnitude of the estimated effect smaller (i.e., closer to zero).

[15] To account for the possibility that the public is responding to visible evidence of government action that is not reflected in the reports, we run a robustness check in Appendix H that includes a control for air pollution coverage in local state-controlled media, which reliably highlights evidence that the local government is effectively addressing the air pollution problem. Like the reports, the media measure also does not have a significant negative relationship with the search index and does not meaningfully affect the other variables.

[16] Lagging the search index prevents short term disturbances to NO_2 levels (such as random weather phenomena) from causing correlated errors, but error correlation may still occur due to unmeasured factors that persist.

Table 1: SEM summary results

	Feedback		No feedback	
	(1)	(2)	(3)	(4)
Outcome: Search Index$_{t\text{-}1}$				
$NO_{2,t\text{-}1}$	0.044***	0.044***	0.045***	0.044***
	(0.006)	(0.006)	(0.006)	(0.006)
$\Delta NO_{2,t\text{-}1}$	0.110***	0.105***	0.078***	0.078***
	(0.015)	(0.015)	(0.015)	(0.015)
Reports$_{t\text{-}1}$	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Dependent Variable: Reports				
$NO_{2,t\text{-}1}$	0.202†	0.205†	0.188†	0.204†
	(0.107)	(0.079)	(0.107)	(0.107)
$\Delta NO_{2,t\text{-}1}$	0.472†	0.471†	0.490†	0.472†
	(0.266)	(0.266)	(0.266)	(0.266)
Search index$_{t\text{-}1}$	0.296	0.294	0.302	0.295
	(0.307)	(0.307)	(0.307)	(0.307)
Dependent Variable: NO_2				
Reports	-0.007†	-0.007*	-0.008*	-0.008*
	(0.004)	(0.004)	(0.004)	(0.004)
Search index$_{t\text{-}1}$	-0.348***	-0.186***	-0.262***	-0.114**
	(0.045)	(0.043)	(0.038)	(0.036)
Spillover	no	yes	no	yes
Estimator	MLE	MLE	MLE	MLE
Akaike (AIC)	79082.18	84984.51	79108.49	85003.77
Bayesian (BIC)	79513.54	85420.46	79535.26	85435.13
R^2 (Search Index eqn.)	0.82	0.82	0.82	0.82
R^2 (Reports eqn.)	0.26	0.26	0.26	0.26
R^2 (No_2 eqn.)	0.96	0.97	0.96	0.97
Observations (per eqn.)	727	727	727	727
Note:	$^\dagger p < 0.1$; $^*p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$			

In Table 1, we compare models that account for feedback (models 1 and 2) to models that disregard it (models 3 and 4).[17] While models 1 and 2 assume that the search index and NO_2 have correlated errors, models 3 and 4 assume each equation is an independent regression. The results are supportive of the feedback dynamic we theorize in two key respects. First, the search index's estimated

[17] For the control variable estimates, see Table D1.

effect on NO_2 is smaller in the models that ignore feedback, which is consistent with the bias we expect feedback to cause. Second, the models that assume correlated errors have better relative fit than their counterparts, as can be seen by their lower Akaike information criterion (AIC) and Bayesian information criterion (BIC) values.[18]

How substantively meaningful is this responsiveness? Depending on how we account for spillover, our results suggest that a one standard deviation increase in public concern leads to a reduction in local NO_2 by roughly 20 to 40 $\mu g/m^3$ the following year, which is a 3 to 6 percent change for the average observation. China's air pollution levels are so far above what is generally considered to be safe that no amount of public concern is likely to bring about safe air in the near future.[19] Even so, the effect is large enough to affect public welfare even in the short term. A decrease of 20 to 40 $\mu g/m^3$ of NO_2 is perceptible and has been found to be sufficient to reduce people's self-reported levels of discomfort (Amundsen, Klaeboe, and Fyhri 2008; Klaeboe, Amundsen, and Fyhri 2008). The size of this effect also suggests near term impacts on public health. While estimating public health impacts is beyond the scope of this paper, an annual decrease of 20 to 40 $\mu g/m^3$ would likely lead to a small but significant reduction in mortality rates even within the three years of this study—and the impacts would be profound over time (Zanobetti and Schwartz 2009).

[18] There appears not to be correlated errors between the reports and NO_2, likely because the feedback dynamic between them is far weaker than with the search index. Models that assume error correlation between the reports and NO_2 have poorer fit than the models in Table 1 as measured by their AIC and BIC values.
[19] The average NO_2 level for the cities in our study is 627 $\mu g/m^3$. For comparison, the American Government considers NO_2 annual exposure over 28 $\mu g/m^3$ to be dangerous.

8 DISCUSSION

The responsiveness aspect of our model builds neatly upon our current understanding of authoritarian responsiveness. Extant scholarship has found limited, ad hoc responsiveness in China, but has provided no clear picture on whether it is substantively meaningful for the general public. Our findings suggest that these instances of responsiveness aggregate into meaningful outcomes in this issue area. In other words, we find that substantive responsiveness exists in an authoritarian system. How responsiveness varies across issue areas remains an open empirical question, but we speculate that substantive responsiveness exists in other issue domains that can be influenced by local actors and have observable outcomes.

Outcomes-based feedback is perhaps our more striking finding, as it is at odds with the thermostatic model. Resolving this contradiction is a task for future scholarship, but we briefly discuss two potential explanations here. One possibility is that outcomes-based responsiveness is a feature of authoritarianism. Perhaps China's heavy media censorship deprives the public of credible signals regarding the level of government action mitigating air pollution. It may simply not be possible for citizens in such a system to respond to anything other than what they can directly perceive. However, we do not find this explanation very convincing in the context of local air pollution. While China's information environment is highly restricted, there are nevertheless avenues through which citizens can gauge the level of government action. For example, the reports—which we find to have a significant effect on local air pollution—are publicly available. More generally, many of the immediate consequences of increased government action, such as an exodus of polluting local employers, can be observed by citizens even without the aid of independent media reporting.

The explanation we find more plausible is that outcomes-based responsiveness is a feature of local level politics. Local outcomes are often observable and have clear, direct impacts on citizens' lives. This is certainly true of air pollution, which citizens suffer from with every breath they take. At the national level, however, outcomes tend to be more remote and harder to discern. It may be that public concern responds to whatever happens to be the most accessible, seemingly reliable indicator of how well a problem is being addressed.

Appendices

A. Public Concern

The extent to which other issues are competing for the public's attention. The public has limited attention and cannot devote equal amounts of effort to addressing all the problems it faces (McCombs 2004). When the public faces other pressing problems, such as rising unemployment or crime, it will necessarily devote less attention to air pollution, even if citizens' beliefs that air pollution levels are too high does not change.

Public concern is also a function of the public's awareness of air pollution's health effects. Breathing polluted air causes immediate physical discomfort, but the long term health risks of exposure are not self-evident. As W. Li, Liu, and Li (2012) conclude based on case studies on environmental activism in China, the public's perceived need for government action is driven not only by its awareness of environmental degradation, but also by its knowledge of the long term health risks posed by pollution—and its negative effect on property values. Knowledge of pollution's long term health consequences has also been identified as a key factor driving online mobilization and environmental activism in China (Fedorenko and Sun 2016).

B. Government Action

Government action is driven in part by pressure on local officials from upper levels of government—particularly the national level. Much of this pressure is exerted through the cadre promotion system. In general, the career incentives built into China's political system lead cadres to pursue a range of objectives—including maximize revenue and economic development and strengthening personal connections with high level officials—at the expense of environmental protection (Hillman 2010; Landry 2008). Furthermore, municipal leaders are typically only assigned to a city for three to four years before being promoted or transferred, which disincentivizes them from making investments that yield long-term environmental while imposing short-term costs (Eaton and Kostka 2014).

The anti-environmental incentives built into China's cadre promotion system are offset to some extent by national pro-environmental policies, which take the form of carrots and sticks. An example of the former is the national government's subsidies for coal plant improvements that reduce sulfur emissions (Xiying Liu, Lin, and Zhang 2016). In the latter case, the national Ministry of Environmental Protection has periodically issued mandates intended to pressure local officials to reduce local emissions (Wu et al. 2017).

Government action is also a function of the composition of the local economy, which determines the difficulty of reducing air pollution emissions. The difficulties officials face are both technical and political. On the technical side, cities that depend on more pollution-inelastic industries have a harder time reducing emissions (Kanada et al. 2013), and pollution abatement costs are generally lower for large scale industries and regions that depend on low grade coal for electricity (L. Dong et al. 2015). Politically, polluters are harder to regulate when they have more leverage over the city government by being a major employer, a state owned enterprise, or near bankruptcy (Lorentzen, Landry, and Yasuda 2014; H. Wang et al. 2003; Zhan Wang and Dear 2017).

C. AIR POLLUTION

The total amount of local economic activity is the dominant factor determining a city's air pollution level (Lin et al. 2014; Y. Liu et al. 2017). Combustion processes—such as those used in automobile engines, electricity generation, and industry—are the primary sources of the major air pollutants in Chinese cities, such as NO_2, sulfur dioxide, and particulate matter (Chan and Yao 2008; Jiang, Lin, and Lin 2014; Qiu et al. 2014).

Air pollution is also a function of the composition of the local economy. Some industries are more pollution-intensive than others, and pollution intensive activities are more prevalent in some cities and regions (Y. Zhou, Zhu, and He 2017, 12–14). Along with the industries themselves, the local sources of electricity are important determinants of air pollution. China has made some progress in recent years reducing its dependence on coal, but that progress has been geographically uneven. The types and grades of coal cities have easy access to also varies by province and has a substantial impact on emissions (Ma et al. 2016; Xu et al. 2017). Fixed power plant characteristics, such as boiler size, affect their efficiency and pollution emissions as well (Xu et al. 2017).

A third determinant of local pollution is spillover from a city's neighbors. The amount of spillover depends on the emissions output of the neighbors as well as geography and climate. It also varies by pollutant. NO_2 has low spillover relative to other common air pollutants. It typically stays in the troposphere for a few days or less, limiting how far it can travel (Lee et al. 2014). The proportion of a city's NO_2 from spillover is likely around 10 percent (Jeong et al. 2017). In contrast, pollutants like fine grain particulate mater ($PM_{2.5}$) stay in the troposphere several times longer (Y. Liu et al. 2017). Spillover may account for around 20 to 30 percent of city's total $PM_{2.5}$ concentration (Chan and Yao 2008; B. Zhou et al. 2015).

Geography and climate are a fourth factor affecting air pollution. The topography surrounding a city affects how much of the locally produced pollution accumulates before dissipating, as well as influencing the spillover between neighbors. Natural barriers such as mountain ranges can concentrate emissions is certain areas while shielding others (Chan and Yao 2008). Climate is also significant. Precipitation, temperature, and humidity all affect how long pollutants remain in the troposphere, which in turn affects how much pollution accumulates in a city before dispersing and how far the wind can carry it (Jeong et al. 2017; B. Zhou et al. 2015). Wind direction, strength, and consistency over the course of a year also affect the distribution of emissions after they have been produced (Y. Liu et al. 2017; B. Zhou et al. 2015).

D. SEM Results with Controls

Table D1 SEM results with Controls

	Feedback		No feedback	
	(1)	(2)	(3)	(4)
Dependent Variable: Search Index$_{t\text{-}1}$				
Search index$_{t\text{-}2}$	1.113***	1.114***	1.113***	1.113***
	(0.023)	(0.023)	(0.023)	(0.023)
$NO_{2,t\text{-}1}$	0.044***	0.044***	0.045***	0.044***
	(0.006)	(0.009)	(0.006)	(0.006)
$\Delta NO_{2,t\text{-}1}$	0.110***	0.105***	0.078***	0.078***
	(0.015)	(0.015)	(0.015)	(0.015)
Reports$_{t\text{-}1}$	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Prov. fixed effects	yes	yes	yes	yes
Dependent Variable: Reports				
Reports$_{t\text{-}1}$	0.357***	0.357***	0.357***	0.357***
	(0.037)	(0.037)	(0.037)	(0.037)
National reports	0.241	0.241	0.237	0.241
	(0.266)	(0.266)	(0.266)	(0.266)
$NO_{2,t\text{-}1}$	0.202†	0.205†	0.188†	0.204†
	(0.107)	(0.079)	(0.107)	(0.107)
$\Delta NO_{2,t\text{-}1}$	0.472†	0.471†	0.490†	0.472†
	(0.266)	(0.266)	(0.266)	(0.266)
Search index$_{t\text{-}1}$	0.296	0.294	0.302	0.295
	(0.307)	(0.307)	(0.307)	(0.307)
Prov. fixed effects	yes	yes	yes	yes
Dependent Variable: NO_2				
$NO_{2,t\text{-}1}$	0.874***	0.731***	0.861***	0.715***
	(0.013)	(0.017)	(0.013)	(0.017)
Spillover		2.362***		2.464***
		(0.169)		(0.196)
ΔGRP	0.716***	0.452***	0.923***	0.603***
	(0.157)	(0.145)	(0.159)	(0.145)
National reports	-0.237***	-0.192***	-0.171***	-0.142***
	(0.029)	(0.027)	(0.029)	(0.027)
Reports	-0.007†	-0.007*	-0.008*	-0.008*
	(0.004)	(0.004)	(0.004)	(0.004)
Search index$_{t\text{-}1}$	-0.348***	-0.186***	-0.262***	-0.114**
	(0.045)	(0.043)	(0.038)	(0.036)
GRP percap (ln)	0.022*	0.033***	0.022*	0.033***
	(0.008)	(0.008)	(0.008)	(0.008)
Prov. fixed effects	yes	yes	yes	yes
Estimator	MLE	MLE	MLE	MLE
Akaike (AIC)	79082.18	84984.51	79108.49	85003.77
Bayesian (BIC)	79513.54	85420.46	79535.26	85435.13
R^2 (Search Index eqn.)	0.82	0.82	0.82	0.82
R^2 (Reports eqn.)	0.26	0.26	0.26	0.26
R^2 (No_2 eqn.)	0.96	0.97	0.96	0.97
Observations (per eqn.)	727	727	727	727
Note:	$^{\dagger}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$			

E. Robustness Checks for Spillover

Table E1: Alternate SEM's controlling for spillover effects

	1	2	3	4
Dependent Variable: Search Index$_{t\text{-}1}$				
Search index$_{t\text{-}2}$	1.113***	1.113***	1.113***	1.113***
	(0.024)	(0.024)	(0.033)	(0.033)
$NO_{2,t\text{-}1}$	0.044***	0.044***	0.044***	0.044***
	(0.006)	(0.006)	(0.009)	(0.009)
$\Delta NO_{2,t\text{-}1}$	0.078***	0.078***	0.078***	0.078***
	(0.016)	(0.016)	(0.022)	(0.022)
Reports$_{t\text{-}1}$	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Prov. fixed effects	yes	yes	yes	yes
Dependent Variable: Reports				
Reports$_{t\text{-}1}$	0.357***	0.357***	0.357***	0.357***
	(0.038)	(0.038)	(0.063)	(0.063)
National reports	0.237	0.237	0.237	0.237
	(0.276)	(0.276)	(0.275)	(0.275)
$NO_{2,t\text{-}1}$	0.194†	0.194†	0.194*	0.194*
	(0.109)	(0.109)	(0.079)	(0.079)
$\Delta NO_{2,t\text{-}1}$	0.480†	0.480†	0.480*	0.480*
	(0.273)	(0.273)	(0.236)	(0.236)
Search index$_{t\text{-}1}$	0.304	0.304	0.304	0.304
	(0.319)	(0.319)	(0.451)	(0.451)
Prov. fixed effects	yes	yes	yes	yes
Dependent Variable: NO_2				
$NO_{2,t\text{-}1}$	0.861***	0.715***	0.861***	0.715***
	(0.013)	(0.017)	(0.021)	(0.059)
Spillover		2.460***		2.460***
		(0.203)		(0.557)
ΔGRP	0.921***	0.602***	0.921**	0.602**
	(0.176)	(0.163)	(0.262)	(0.201)
National reports	-0.171***	-0.142***	-0.171†	-0.142†
	(0.031)	(0.028)	(0.096)	(0.071)
Reports	-0.008*	-0.008*	-0.008	-0.008*
	(0.004)	(0.004)	(0.005)	(0.003)
Search index$_{t\text{-}1}$	-0.262***	-0.113**	-0.262***	-0.113†
	(0.044)	(0.042)	(0.055)	(0.061)
GRP percap (ln)	0.022*	0.032*	0.022*	0.032*
	(0.009)	(0.008)	(0.009)	(0.012)
Prov. fixed effects	yes	yes	yes	yes
Clustered standard errors	no	no	yes	yes
Estimator	OLS	OLS	OLS	OLS
R^2 (Search Index eqn.)	0.81	0.81	0.81	0.81
R^2 (Reports eqn.)	0.22	0.22	0.22	0.22
R^2 (NO_2 eqn.)	0.96	0.97	0.96	0.97
Observations (per eqn.)	7272	727	727	727
Note:	$^{\dagger}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$			

F. SAR Models

The SAR model is expressed as follows, where *$\rho W(NO_2)$* represents the effect of pollution spillover on the dependent variable. *W* is the spatial weights matrix representing city *i's* neighbors and ρ is its coefficient estimate for the effect of pollution spillover on the dependent variable. *t* represents the year and $\hat{\gamma}$ is a vector of control variable estimates.

$$\mathrm{NO2}_{\mathrm{i,t}} = \alpha_{4,0} + \rho \mathrm{W}\left(\mathrm{NO2}_{\mathrm{i,t}}\right) + \beta_{4,1}\mathrm{Reports}_{\mathrm{i,t}} + \beta_{4,2}\mathrm{Search.\,Index}_{\mathrm{i,t-1}} + \widehat{\gamma_4} + \mathrm{e}_{4,\mathrm{i,t}} \qquad \text{(F1)}$$

Table F1 shows the coefficient estimates and standard errors for the above equation with four different neighborhood definitions. The definitions include all observations that are within the radius, as measured from a city's center point to the center point of other cities. These coefficient estimates do not reflect the spatial weights and are not directly interpretable. Note that the ρ is around 0.1 in all four models, which is consistent with our expectation that roughly 10 percent of a city's NO_2 is attributable to spillover.

Table F2 shows the total impacts of each variable on NO_2 along with the significance levels from Table F1. The impacts for the search index and reports on NO_2 are comparable to the SEM estimates in Table 1.

Table F1: SAR model coefficients

	Dependent variable:			
	NO_2			
	(1)	(2)	(3)	(4)
$NO_{2,t\text{-}1}$	0.810***	0.826***	0.849***	0.858***
	(0.012)	(0.011)	(0.011)	(0.010)
ΔGRP	0.416**	0.407**	0.409**	0.409**
	(0.138)	(0.141)	(0.142)	(0.143)
National reports	−0.174***	−0.173***	−0.176***	−0.177***
	(0.031)	(0.031)	(0.031)	(0.032)
Reports	−0.012***	−0.012***	−0.012***	−0.012***
	(0.003)	(0.003)	(0.003)	(0.003)
Search index$_{t\text{-}1}$	−0.084*	−0.093*	−0.104**	−0.109**
	(0.037)	(0.038)	(0.038)	(0.038)
GRP percap (ln)	0.011†	0.015*	0.014*	0.013*
	(0.006)	(0.006)	(0.006)	(0.006)
Neighborhood radius	200 km	300 km	400 km	500 km
Prov. fixed effects	no	no	no	no
Estimator	MLE	MLE	MLE	MLE
ρ	0.132	0.119	0.094	0.086
Observations	880	880	880	880
Log Likelihood	−5,198.878	−5,210.873	−5,221.515	−5,226.439
σ^2	7,895.043	8,132.103	8,338.732	8,434.504
Akaike Inf. Crit.	10,415.760	10,439.750	10,461.030	10,470.880
Wald Test (df = 1)	89.768***	65.862***	42.582***	32.432***
LR Test (df = 1)	87.103***	63.113***	41.829***	31.981***
Note:	†p< 0.1; *p<0.05; **p<0.01; ***p<0.001			

Table F2: SAR model impacts

	Dependent variable: NO$_2$			
	(1)	(2)	(3)	(4)
NO$_{2,t\text{-}1}$	0.931***	0.938***	0.936***	0.939***
ΔGRP	0.478**	0.462**	0.451**	0.447**
National reports	-0.201***	-0.197***	-0.194***	-0.193***
Reports	-0.013***	-0.014***	-0.013***	-0.013***
Search index$_{t\text{-}1}$	-0.096*	-0.106*	-0.115**	-0.119**
GRP percap (ln)	0.013†	0.017*	0.016*	0.014*
Neighborhood Radius	200 km	300 km	400 km	500 km
Note:	†p< 0.1; *p<0.05; **p<0.01; ***p<0.001			

G. RESULTS WITHOUT REPORTS' EFFECT ON NO_2

*Figure G1: Results without reports' effect on NO_2. †$p<0.1$; *$p<0.05$; **$p<0.01$; ***$p<0.001$. N = 727.*

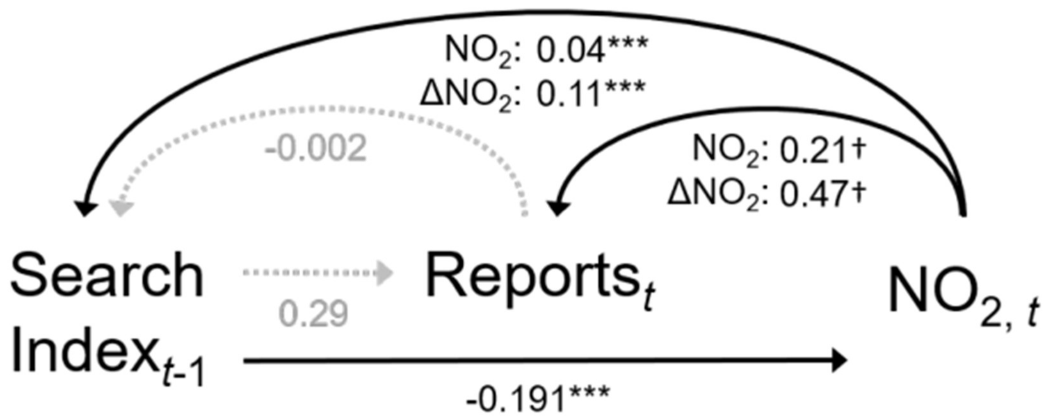


Table G1: Results without reports' effect on NO_2 summary

	Feedback		No feedback	
	(1)	(2)	(3)	(4)
Dependent Variable: Search Index$_{t\text{-}1}$				
$NO_{2,t\text{-}1}$	0.044^{***}	0.044^{***}	0.044^{***}	0.044^{***}
	(0.006)	(0.006)	(0.006)	(0.006)
$\Delta NO_{2,t\text{-}1}$	0.111^{***}	0.106^{***}	0.078^{***}	0.078^{***}
	(0.015)	(0.015)	(0.015)	(0.015)
Reports$_{t\text{-}1}$	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Dependent Variable: Reports				
$NO_{2,t\text{-}1}$	$0.203^{\dagger}$	$0.204^{\dagger}$	$0.191^{\dagger}$	$0.203^{\dagger}$
	(0.107)	(0.107)	(0.107)	(0.107)
$\Delta NO_{2,t\text{-}1}$	$0.470^{\dagger}$	$0.469^{\dagger}$	$0.484^{\dagger}$	$0.469^{\dagger}$
	(0.266)	(0.266)	(0.266)	(0.266)
Search index$_{t\text{-}1}$	0.296	0.294	0.299	0.295
	(0.307)	(0.307)	(0.307)	(0.307)
Dependent Variable: NO_2				
Search index$_{t\text{-}1}$	-0.353^{***}	-0.191^{***}	-0.267^{***}	-0.118^{**}
	(0.045)	(0.043)	(0.038)	(0.036)
Spillover	no	yes	no	yes
Estimator	MLE	MLE	MLE	MLE
Akaike (AIC)	79085.60	84984.51	79112.83	85008.47
Bayesian (BIC)	79516.96	85420.46	79539.60	85439.83
R^2 (Search Index eqn.)	0.82	0.82	0.82	0.82
R^2 (Reports eqn.)	0.26	0.26	0.26	0.26
R^2 (No_2 eqn.)	0.96	0.97	0.96	0.97
Observations (per eqn.)	727	727	727	727

Note: $^{\dagger}p< 0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

H. Controlling for State Media Coverage of Government Action

The models in Table H1 include a state media variable in the search index equation and are otherwise identical to those in Table 1. We use this variable to check whether public concern really is responding directly to government action (as the thermostatic model predicts), but is not responding to the particular aspect of government action represented by the government reports. Local state media is propaganda---its coverage of air pollution typically portrays the issue as one that the local government is effectively addressing. If public concern is responding to government action by way of what citizens see in state media, state media should have a significant negative relationship with public concern.[20]

As Table H1 shows, state media coverage of air pollution does not have a negative relationship with the search index while the reports' effect on the search index remains insignificant. In fact, the state media's estimated effect is *positive* and highly significant. We speculate that this is because state media is responding to public concern. That is, when the public becomes more worried about air pollution, state media devotes more time to portraying the local government as having the problem under control.[21] That state media lacks a negative relationship with the search index is further evidence that the public concern is not directly responding to government action.

[20] The state media measure is the total number of articles in each city's daily party newspaper which contains at least one keyword related to air pollution over the course of a year. The key words are *Air Quality* (空气质量), *Air Pollution* (空气污染), *Air Pollution* (大气污染), *$PM_{2.5}$, PM_{10}, and NO_2*. This list of keywords is shorter than the list for government work reports because these searches had to be performed through a library database. The terms not related specifically to air pollution—*clean energy, environmental pollution, environmental protection, green economy, and new energy*—produced too many matches for the database to report. Three others—*atmospheric protection*, *emissions*, and *emissions reduction*—produced too many matches and tended to refer to carbon dioxide emissions as opposed to local air pollution. Several other terms are highly technical and produced negligible numbers of matches—*nitrogen dioxide*, *particulate matter*, and *NO_x*.

[21] It is extremely unlikely that the media coverage itself is causing public concern to increase in this case; the coverage is intended to reduce public concern without raising awareness. Upon reading a random selection of 300 of the 12,107 newspaper articles in our sample that include one or more of the search terms, we found none that discussed air pollution increases over time, the health dangers posed by long-term exposure, which firms were guilty of flouting environmental rules or were especially egregious polluters, or which government officials were most responsible for addressing pollution problems. Instead, the articles consistently suggested that air pollution was not a serious problem and—to the extent it was a problem—was already being effectively addressed by the government. Many of the articles claimed that air pollution had decreased year on year, or that the city in which the newspaper was based had the cleanest air in its province or region. Many others highlighted efforts by city governments to address air pollution, such as investing in new monitoring equipment.

Table H1: Summary results including control for local state media coverage

	Feedback		No feedback	
	(1)	(2)	(3)	(4)
Dependent Variable: Search Index$_{t\text{-}1}$				
$NO_{2,t\text{-}1}$	0.040^{***}	0.040^{***}	0.041^{***}	0.041^{***}
	(0.006)	(0.006)	(0.006)	(0.006)
$\Delta NO_{2,t\text{-}1}$	0.124^{***}	0.119^{***}	0.088^{***}	0.088^{***}
	(0.014)	(0.014)	(0.015)	(0.015)
Reports$_{t\text{-}1}$	-0.001	-0.001	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)
State media$_{t\text{-}1}$	0.636^{***}	0.632^{***}	0.609^{***}	0.608^{***}
	(0.074)	(0.075)	(0.077)	(0.077)
Dependent Variable: Reports				
$NO_{2,t\text{-}1}$	$0.203^{\dagger}$	$0.205^{\dagger}$	$0.193^{\dagger}$	$0.203^{\dagger}$
	(0.107)	(0.107)	(0.107)	(0.107)
$\Delta NO_{2,t\text{-}1}$	$0.471^{\dagger}$	$0.470^{\dagger}$	$0.486^{\dagger}$	$0.472^{\dagger}$
	(0.266)	(0.266)	(0.266)	(0.266)
Search index$_{t\text{-}1}$	0.296	0.294	0.298	0.295
	(0.307)	(0.307)	(0.307)	(0.307)
Dependent Variable: NO_2				
Reports	$-0.007^{\dagger}$	-0.007^{*}	-0.008^{*}	-0.008^{*}
	(0.004)	(0.004)	(0.004)	(0.004)
Search index$_{t\text{-}1}$	-0.352^{***}	-0.193^{***}	-0.263^{***}	-0.114^{**}
	(0.045)	(0.043)	(0.038)	(0.036)
Spillover	no	yes	no	yes
Estimator	MLE	MLE	MLE	MLE
Akaike (AIC)	85540.75	91441.65	85577.46	91469.10
Bayesian (BIC)	85976.70	91882.18	86008.82	91905.04
R^2 (Search Index eqn.)	0.83	0.83	0.83	0.83
R^2 (Reports eqn.)	0.26	0.26	0.26	0.26
R^2 (No_2 eqn.)	0.96	0.97	0.96	0.97
Observations (per eqn.)	727	727	727	727

Note: $^{\dagger}p< 0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

I. Government Work Report Key Words

These are the keywords used to identify air pollution-related paragraphs in the government work reports with English translations. Each term is equally weighted in our measurement.

Air Pollution (空气污染), Air Pollution (大气污染), Air Quality (空气质量), Atmospheric Protection (大气保护), Emissions (排放), Emissions Reduction (减排), Clean Energy (清洁能源), Environmental Pollution (环境污染), Environmental Protection (环境保护), Green Economy (绿色经济), New Energy (新能源), Nitrogen Dioxide (二氧化氮), NO_2, NO_x, Particulate Matter (颗粒物), $PM_{2.5}$, and PM_{10}.

J. CASE SELECTION

Our analysis uses all observations for which data are available. Notably, our analysis excludes the province-level municipalities (Beijing, Tianjin, Shanghai, and Chongqing) due to the unavailability of comparable search index data for those cities.[22] The following series of figures shows the location of all cities in our sample (Figure J1), and the locations of the cities for each year of our data (Figures J2 – J4).

As can be seen in these figures, the number of cities in our sample increases each year. This pattern is driven almost entirely by the availability of the government work reports for each city.[23] We address the possibility that the availability of the reports could be causing some sort of bias in Appendix K. It is possible, for instance, that cities only begin releasing reports when they feel the need to be responsive to the public.

[22] Because of their special administrative status, Baidu's search index considers them to be provinces.
[23] Only two of the 819 possible observations for the 273 cities in our sample are missing due to the lack of Yearbook data.

Figure J1: All cities in sample. The shaded areas represent the 273 cities that are in our sample for at least one year.

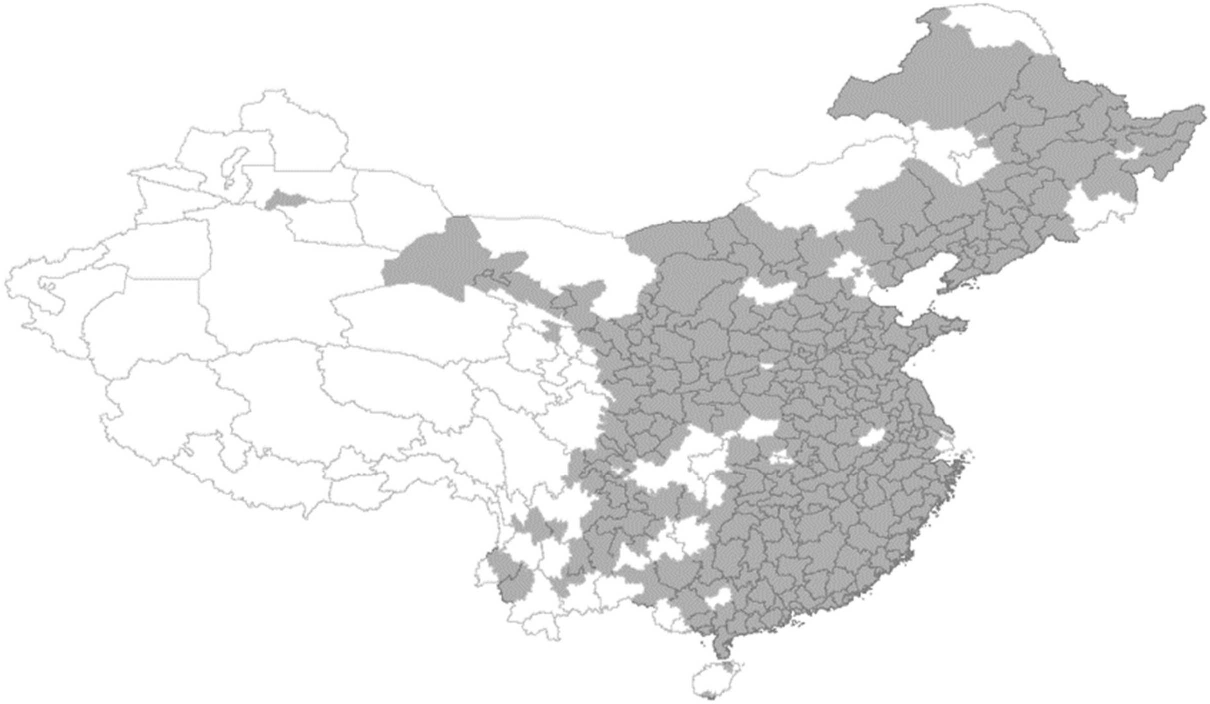


Figure J2: Cities in sample for 2013. The shaded areas represent the 2012 cities that are in our sample for 2013.

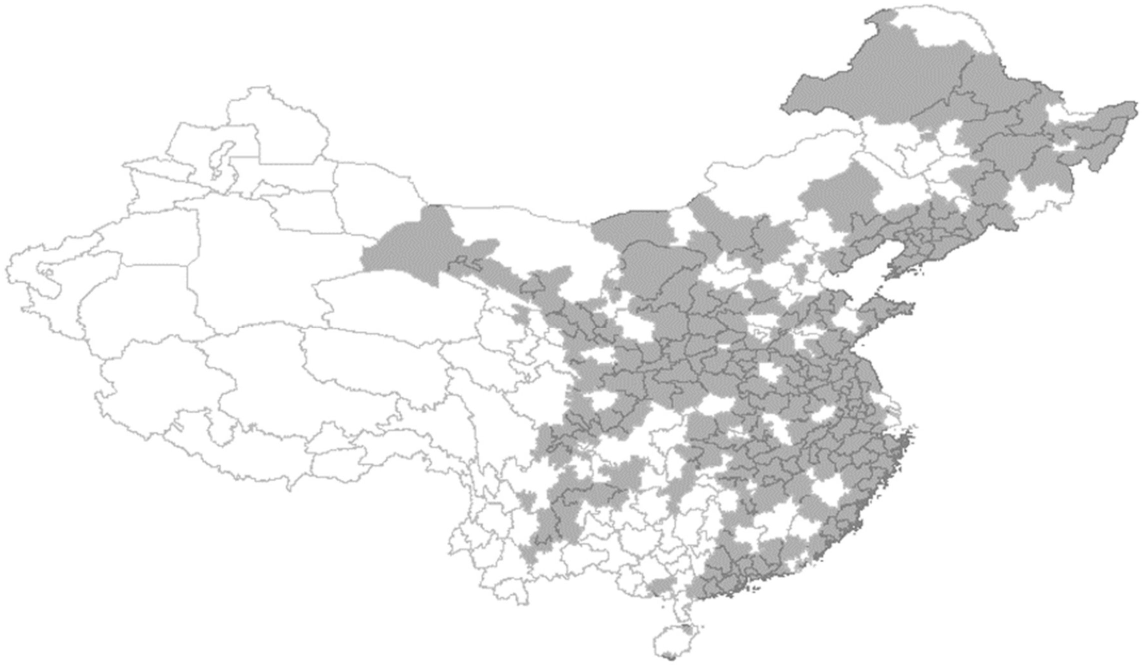


Figure J3: Cities in sample for 2014. The shaded areas represent the 249 cities that are in our sample for 2014.

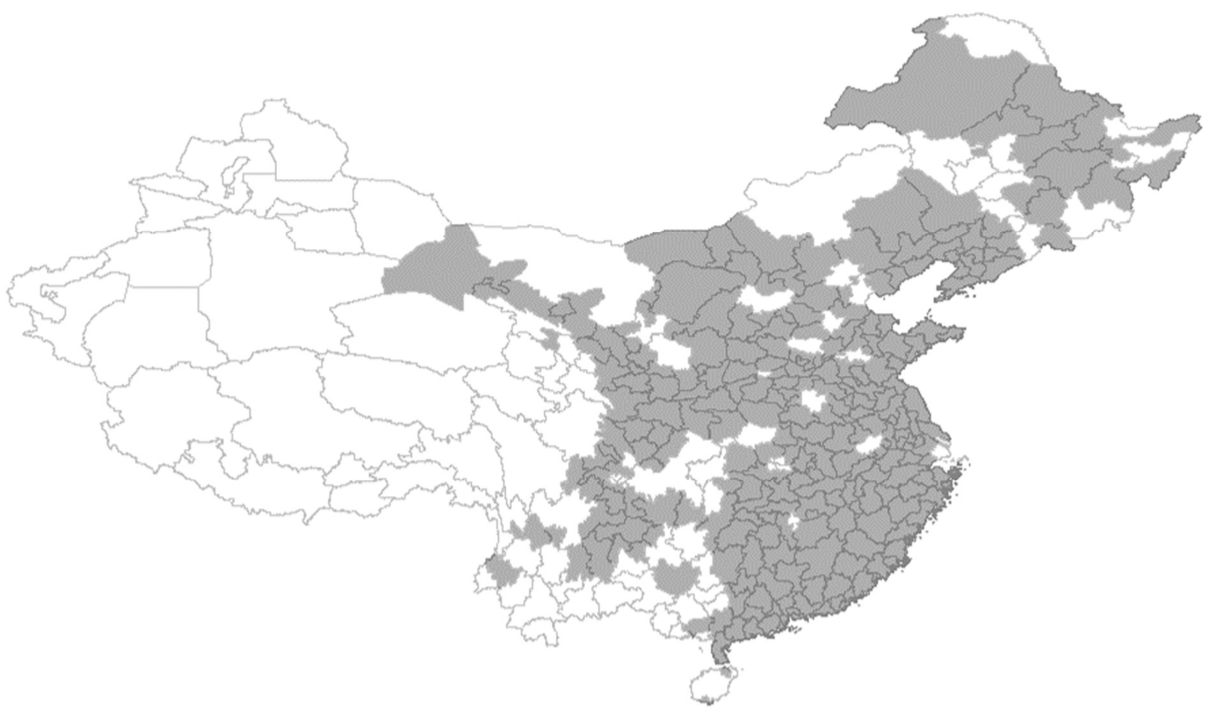
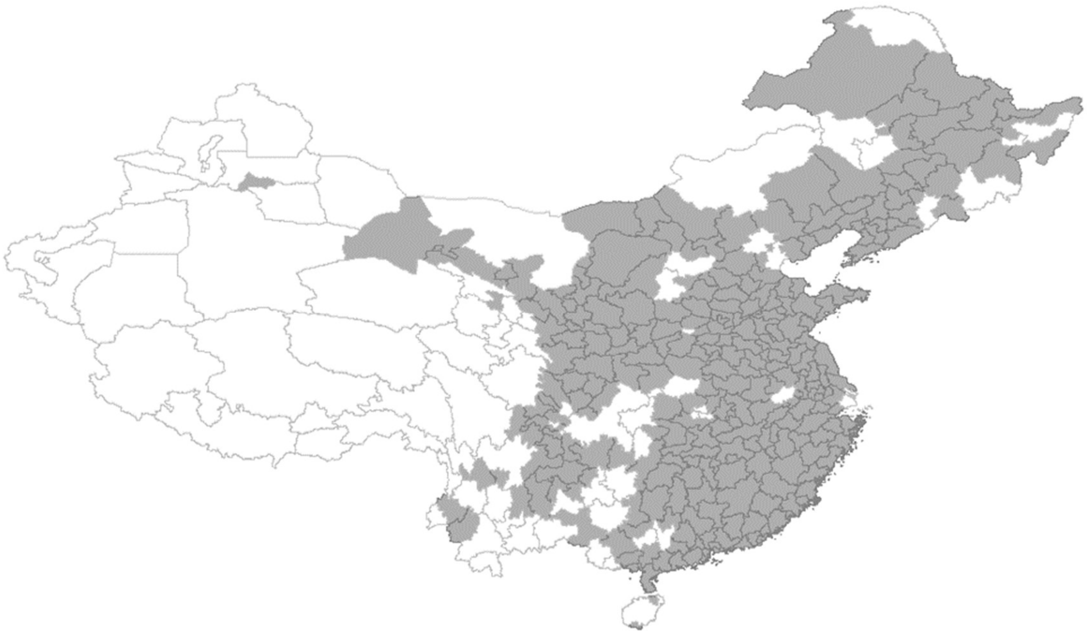


Figure J4: Cities in sample for 2015. The shaded areas represent the 266 cities that are in our sample for 2015.



K. SEM'S EXCLUDING THE REPORTS MEASURE

Table K1 shows the summarized results for the models in Table 1 without any reports measures.[24] Excluding the reports allows us to increase the sample size to 817 observations (of the 819 possible for the 273 cities in our analysis.). If the increasing availability of the reports over time were biasing the results in some way, then these estimates should be noticeably different from their counterparts in Table 1. What we see, however, is that the relationship between the search index and NO_2 remains virtually unchanged by the increased sample size.

Table K1: Results summary excluding the reports variable

	Feedback		No feedback	
	(1)	(2)	(3)	(4)
Outcome: Search Index$_{t\text{-}1}$				
$NO_{2,t\text{-}1}$	0.041^{***}	0.044^{***}	0.042^{***}	0.042^{***}
	(0.006)	(0.006)	(0.006)	(0.006)
$\Delta NO_{2,t\text{-}1}$	0.105^{***}	0.101^{***}	0.077^{***}	0.077^{***}
	(0.015)	(0.014)	(0.014)	(0.014)
Dependent Variable: NO_2				
Search index$_{t\text{-}1}$	-0.368^{***}	-0.177^{***}	-0.293^{***}	-0.110^{**}
	(0.045)	(0.043)	(0.038)	(0.036)
Spillover	no	yes	no	yes
Estimator	MLE	MLE	MLE	MLE
Akaike (AIC)	63556.19	70189.25	63579.75	70206.72
Bayesian (BIC)	63843.24	70481.00	63862.09	70493.77
R^2 (Search Index eqn.)	0.82	0.82	0.82	0.82
R^2 (No_2 eqn.)	0.96	0.97	0.96	0.97
Observations (per eqn.)	817	817	817	817

Note: $^{\dagger}p< 0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

[24] The national level reports control is still a control variable for the NO2 equation.

L. NO_2 Satellite Data

Our NO_2 data are from the European Space Agency's DOMINO dataset (version 2), which is derived from the daily overpass measurements of the OMI sensor on the AURA satellite using the KNMI atmospheric model. The grid's resolution is 0.125 by 0.125 degrees (around 12.5 by 12.5 km at the equator) and extends from 2005 past 2015. Most cities straddle multiple grid spaces, so we calculate municipal NO_2 concentrations as the weighted means of the grid spaces each city occupies. To calculate the weighted means, we up-sample the monthly grids to 0.0125 by 0.0125 degrees using bilinear interpolation[25] and take the mean of all grid squares that are partially or entirely within each city's administrative boundary.[26] We then annualize the monthly means and remove any observation that is missing one or more months.[27]

The OMI-derived NO_2 grid has imperfect spatial coverage, and its gaps are not consistent from year to year, particularly after 2007 when OMI suffered a partial malfunction (Schneider 2015). Missing OMI data would reduce our sample size by around 100 observations and create a significant number of holes in our dataset. We therefore substitute the missing NO_2 values with rescaled values from the European Space Agency's METOP-A and METOP-B satellite-derived datasets (version 2.3), which are lower resolution but have near total spatial coverage of China.

[25] Bilinear interpolation treats the values associated with the original 0.125 by 0.125 degree (roughly 12.5 by 12.5km) grid spaces as points at the exact center of each grid square and then calculates the values for the smaller 0.0125 by 0.0125 degree (roughly 1.25 by 1.25km) squares as averages of the four closest points weighted by inverse distance. We use this interpolation method because it is conservative; it does not introduce values outside the range of the original data and makes no assumptions about the presence of geographic boundaries (such as mountain ranges) or prevailing winds.

[26] The boundaries are defined by the second administrative level boundary map from the GADM database of Global Administrative Areas (version 2.8), which correspond to China's prefecture and prefecture-equivalent boundaries in 2015.

[27] Air pollution varies substantially by season, but its time series within season is stationary (X. K. Wang and Lu 2006). A missing month of measurements therefore risks biasing an observation.

M. Year Fixed Effects

Table M1 shows the SEM results with year fixed effects included in all three equations and the national reports controls removed.[28] Broadly speaking, these results are consistent with our results in Table 1. However, the key variables in the search index and NO_2 models all have smaller coefficients (though similar standard errors) than in the main results. In several cases, the smaller coefficients push the estimates' significance levels below conventional significance thresholds. These smaller coefficients suggest that temporal variation is an important component of our main results. While it is not possible to perform deep time series analysis with only three time periods, we strongly suspect that public awareness across cities tends to move together over time.

[28] Because the national reports do not vary within a year, they cannot be included in an equation with year fixed effects.

Table M1: Results with year fixed effects

	Dependent variable:			
	Search Index$_{t\text{-}1}$	Reports	NO_2	
	(1)	(2)	(3)	(4)
GRP percap (ln)			0.027**	0.036***
			(0.008)	(0.008)
ΔGRP			0.469*	0.314†
			(0.189)	(0.174)
$NO_{2,t\text{-}1}$	0.032***	0.225*	0.844***	0.713***
	(0.006)	(0.113)	(0.013)	(0.017)
$\Delta NO_{2,t\text{-}1}$	0.027†	0.525†		
	(0.015)	(0.276)		
Reports	−0.001	0.355***		
	(0.002)	(0.038)		
Reports$_{t\text{-}1}$			−0.007	−0.007*
			(0.004)	(0.004)
Search index$_{t\text{-}1}$		0.169	−0.123*	−0.028
		(0.340)	(0.049)	(0.046)
Search index$_{t\text{-}2}$	1.201***			
	(0.025)			
Spillover				2.305***
				(0.204)
Prov. fixed effects	yes	yes	yes	yes
Estimator	OLS	OLS	OLS	OLS
Observations	727	727	727	727
R^2	0.851	0.257	0.966	0.971
Adjusted R^2	0.844	0.224	0.964	0.970
Residual Std. Error	43.360	817.303	90.774	83.474
F Statistic	128.004***	7.756***	611.243***	704.791***
Note:	†p< 0.1; *p<0.05; **p<0.01; ***p<0.001			

N. Province Random Effects

Table N1 uses random province effects instead of fixed effects. The control variable estimates are displayed. With one minor exception, all variables of interest remain significant with estimates comparable to our primary results in Table 1. The exception is ΔNO_2 in Model 2. Substantively, this result is not much different than our primary results with fixed effects. The estimates for Model 2 in this table imply that the reports are responsive to absolute NO_2 levels but not year on year change in NO_2. Model 2's fixed effect counterpart suggests that the reports are responsive to both NO_2 and ΔNO_2.

Table N1: Results with province random effects

	Dependent variable:			
	Search Index$_{t\text{-}1}$	Reports	NO_2	
	(1)	(2)	(3)	(4)
GRP percap (ln)			0.020^{**}	0.026^{***}
			(0.007)	(0.007)
ΔGRP			0.805^{***}	0.645^{***}
			(0.163)	(0.154)
National reports		0.333	-0.183^{***}	-0.153^{***}
		(0.278)	(0.031)	(0.029)
$NO_{2,t\text{-}1}$	0.035^{***}	0.207^{**}	0.893^{***}	0.729^{***}
	(0.004)	(0.065)	(0.007)	(0.017)
$\Delta NO_{2,t\text{-}1}$	0.087^{***}	0.248		
	(0.015)	(0.265)		
Reports			-0.011^{**}	-0.009^{*}
			(0.004)	(0.004)
Reports$_{t\text{-}1}$	-0.002	0.429^{***}		
	(0.002)	(0.036)		
Search index$_{t\text{-}1}$		0.277	-0.204^{***}	-0.106^{*}
		(0.303)	(0.043)	(0.041)
Search index$_{t\text{-}2}$	1.148^{***}			
	(0.023)			
Spillover				1.769^{***}
				(0.161)
Prov. random effects	yes	yes	yes	yes
Estimator	OLS	OLS	OLS	OLS
Observations	727	727	727	727
R^2	0.807	0.205	0.961	0.961
Adjusted R^2	0.806	0.200	0.961	0.961
F Statistic	755.173^{***}	37.222^{***}	$2{,}985.013^{***}$	$2{,}529.691^{***}$
Note:	$^{\dagger}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$			

References

Amundsen, A. H., R. Klaeboe, and A. Fyhri. 2008. “Annoyance from Vehicular Air Pollution: Exposure-Response Relationships for Norway.” *Atmospheric Environment* 42 (33): 7679–7688. https://doi.org/10.1016/j.atmosenv.2008.05.026.

Brady, Anne-Marie, and Wang Juntao. 2009. “China’s Strengthened New Order and the Role of Propaganda.” *Journal of Contemporary China* 18 (October): 767–788. https://doi.org/10.1080/10670560903172832.

Brandt, Loren, and Carsten A. Holz. 2006. “Spatial Price Differences in China: Estimates and Implications.” *Economic Development and Cultural Change* 55 (1): 43–86. https://doi.org/10.1086/505722.

Cai, Yongshun. 2010. *Collective Resistance in China: Why Popular Protests Succeed or Fail*. Stanford, CA: Stanford University Press.

Chan, Chak K., and Xiaohong Yao. 2008. “Air Pollution in Mega Cities in China.” *Atmospheric Environment* 42: 1–42. https://doi.org/10.1016/j.atmosenv.2007.09.003.

Chen, Jidong, Jennifer Pan, and Yiqing Xu. 2016. “Sources of Authoritarian Responsiveness: A Field Experiment in China.” *American Journal of Political Science* 60 (2): 383–400. https://doi.org/10.1111/ajps.12207.

China Internet Network Information Center. 2011. “Statistical Report on Internet Development in China.” January. China Internet Network Information Center. http://www1.cnnic.cn/IDR/ReportDownloads/201302/P020130221391269963814.pdf.

———. 2015. “Statistical Report on Internet Development in China.” January. China Internet Network Information Center. http://cnnic.com.cn/IDR/ReportDownloads/201507/P020150720486421654597.pdf.

Distelhorst, Greg, and Yue Hou. 2017. “Constituency Service under Nondemocratic Rule: Evidence from China.” *The Journal of Politics* 79 (3): 1024–1040. https://doi.org/10.1086/690948.

Dong, Liang, Huijuan Dong, Tsuyoshi Fujita, Yong Geng, and Minoru Fujii. 2015. “Cost-Effectiveness Analysis of China’s Sulfur Dioxide Control Strategy at the Regional Level: Regional Disparity, Inequity and Future Challenges.” *Journal of Cleaner Production* 90: 345–359. https://doi.org/10.1016/j.jclepro.2014.10.101.

Dong, Yanli, Masanobu Ishikawa, Xianbing Liu, and Shigeyuki Hamori. 2011. “The Determinants of Citizen Complaints on Environmental Pollution: An Empirical Study from China.” *Journal of Cleaner Production* 19 (12): 1306–1314. https://doi.org/10.1016/j.jclepro.2011.03.015.

Eaton, Sarah, and Genia Kostka. 2014. “Authoritarian Environmentalism Undermined? Local Leaders’ Time Horizons and Environmental Policy Implementation in China.” *The China Quarterly* 218 (May 2014): 359–380. https://doi.org/10.1017/S0305741014000356.

Fedorenko, Irina, and Yixian Sun. 2016. “Microblogging-Based Civic Participation on Environment in China: A Case Study of the PM 2.5 Campaign.” *Voluntas* 27 (5): 2077–2105. https://doi.org/10.1007/s11266-015-9591-1.

Fontes, Tânia, Peilin Li, Nelson Barros, and Pengjun Zhao. 2017. “Trends of PM2.5 Concentrations in China: A Long Term Approach.” *Journal of Environmental Management* 196: 719–732. https://doi.org/10.1016/j.jenvman.2017.03.074.

Fotheringham, A. Stewart, and Taylor M. Oshan. 2016. “Geographically Weighted Regression and Multicollinearity: Dispelling the Myth.” *Journal of Geographical Systems* 18 (4): 303–329. https://doi.org/10.1007/s10109-016-0239-5.

Ghanem, Dalia, and Junjie Zhang. 2014. "'Effortless Perfection:' Do Chinese Cities Manipulate Air Pollution Data?" *Journal of Environmental Economics and Management* 68 (2): 203–225. https://doi.org/10.1016/j.jeem.2014.05.003.

Gibbons, Stephen, and Henry G. Overman. 2012. "Mostly Pointless Spatial Econometrics?" *Journal of Regional Science* 52 (2): 172–191. https://doi.org/10.1111/j.1467-9787.2012.00760.x.

Göbel, Christian, and Lynette H. Ong. 2012. "Social Unrest in China." London: Europe China Research and Advice Network. http://digitalcommons.ilr.cornell.edu/cgi/viewcontent.cgi?article=1018&context=crs.

Henderson, J. Vernon, Adam Storeygard, and David N. Weil. 2012. "Measuring Economic Growth from Outer Space." *American Economic Review* 102 (2): 994–1028.

Hillman, Ben. 2010. "Factions and Spoils: Examining Political Behavior within the Local State in China." *The China Journal* 64: 1–18.

Jennings, Will. 2009. "The Public Thermostat, Political Responsiveness and Error-Correction: Border Control and Asylum in Britain, 1994-2007." *British Journal of Political Science* 39 (4): 847–870. https://doi.org/10.1017/S000712340900074X.

Jeong, Ukkyo, Jhoon Kim, Hanlim Lee, and Yun Gon Lee. 2017. "Assessing the Effect of Long-Range Pollutant Transportation on Air Quality in Seoul Using the Conditional Potential Source Contribution Function Method." *Atmospheric Environment* 150: 33–44. https://doi.org/10.1016/j.atmosenv.2016.11.017.

Jiang, Liangliang, Chen Lin, and Ping Lin. 2014. "The Determinants of Pollution Levels: Firm-Level Evidence from Chinese Manufacturing." *Journal of Comparative Economics* 42 (1): 118–142. https://doi.org/10.1016/j.jce.2013.07.007.

Jones, Bryan D., Saadia R. Greenberg, Clifford Kaufman, and Joseph Drew. 1977. "Bureaucratic Response to Citizen-Initiated Contacts: Environmental Enforcement in Detroit." *American Political Science Review* 71 (1): 148–165.

Kanada, Momoe, Liang Dong, Tsuyoshi Fujita, Minoru Fujii, Tsuyoshi Inoue, Yujiro Hirano, Takuya Togawa, and Yong Geng. 2013. "Regional Disparity and Cost-Effective SO2 Pollution Control in China: A Case Study in 5 Mega-Cities." *Energy Policy* 61: 1322–1331. https://doi.org/10.1016/j.enpol.2013.05.105.

Kingdon, John W. 1995. *Agendas, Alternatives, and Public Policies*. 2nd ed. New York: Longman.

Klaeboe, R., A. H. Amundsen, and A. Fyhri. 2008. "Annoyance from Vehicular Air Pollution: A Comparison of European Exposure–Response Relationships." *Atmospheric Environment* 42 (33): 7679–7688. https://doi.org/10.1016/j.atmosenv.2008.05.026.

Landry, Pierre F. 2008. "Organized Decentralization." In *Decentralized Authoritarianism in China: The Communist Party's Control of Local Elites in the Post-Mao Era*, 37–79. New York: Cambridge University Press.

Landry, Pierre F., Xiaobo Lü, and Haiyan Duan. 2018. "Does Performance Matter? Evaluating Political Selection Along the Chinese Administrative Ladder." *Comparative Political Studies* 51 (8): 1074–1105. https://doi.org/10.1177/0010414017730078.

Lee, H.-J, S.-W Kim, J. Brioude, O. R. Cooper, G. J. Frost, C.-H. Kim, R. J. Park, M. Trainer, and J.-H. Woo. 2014. "Transport of NOx in East Asia Identified by Satellite and in Situ Measurements and Lagrangian Particle Dispersion Model Simulations." *Journal of Geophysical Research: Atmospheres* 119: 2574–2596. https://doi.org/10.1002/ 2013JD021185.

Li, Hongyan, and Xiaoyun Xin. 2013. "Nitrogen Dioxide (NO2) Pollution as a Potential Risk Factor for Developing Vascular Dementia and Its Synaptic Mechanisms." *Chemosphere* 92 (1): 52–58. https://doi.org/10.1016/j.chemosphere.2013.02.061.

Li, Wanxin, Jieyan Liu, and Duoduo Li. 2012. “Getting Their Voices Heard: Three Cases of Public Participation in Environmental Protection in China.” *Journal of Environmental Management* 98 (1): 65–72. https://doi.org/10.1016/j.jenvman.2011.12.019.

Lin, Gang, Jingying Fu, Dong Jiang, Wensheng Hu, Donglin Dong, Yaohuan Huang, and Mingdong Zhao. 2014. “Spatio-Temporal Variation of PM2.5 Concentrations and Their Relationship with Geographic and Socioeconomic Factors in China.” *International Journal of Environmental Research and Public Health* 11 (1): 173–186. https://doi.org/10.3390/ijerph110100173.

Liu, Jingfang. 2011. “Picturing a Green Virtual Public Space for Social Change: A Study of Internet Activism and Web-Based Environmental Collective Actions in China.” *Chinese Journal of Communication* 4 (2): 137–166. https://doi.org/10.1080/17544750.2011.565674.

Liu, Xianbing, Yanli Dong, Can Wang, and Tomohiro Shishime. 2011. “Citizen Complaints about Environmental Pollution: A Survey Study in Suzhou, China.” *Journal of Current Chinese Affairs - China Aktuell* 40 (3): 193–219. https://doi.org/DOI: ,.

Liu, Xiying, Boqiang Lin, and Yanjiang Zhang. 2016. “Sulfur Dioxide Emission Reduction of Power Plants in China: Current Policies and Implications.” *Journal of Cleaner Production* 113: 133–143. https://doi.org/10.1016/j.jclepro.2015.12.046.

Liu, Yiming, Yingying Hong, Qi Fan, Xuemei Wang, Pakwai Chan, Xiaoyang Chen, Anqi Lai, Mingjie Wang, and Xunlai Chen. 2017. “Source-Receptor Relationships for PM2.5 during Typical Pollution Episodes in the Pearl River Delta City Cluster, China.” *Science of the Total Environment* 596–597: 194–206. https://doi.org/10.1016/j.scitotenv.2017.03.255.

Lo, Carlos Wing Hung, Gerald E. Fryxell, and Wilson Wai Ho Wong. 2006. “Effective Regulations with Little Effect? The Antecedents of the Perceptions of Environmental Officials on Enforcement Effectiveness in China.” *Environmental Management* 38 (3): 388–410. https://doi.org/10.1007/s00267-005-0075-8.

Lo, Carlos Wing Hung, and Gerald Erick Fryxell. 2005. “Governmental and Societal Support for Environmental Enforcement in China: An Empirical Study in Guangzhou.” *Journal of Development Studies* 41 (4): 558–588. https://doi.org/10.1080/00220380500092655.

Lo, Carlos Wing Hung, and Sai Wing Leung. 2000. “Environmental Agency and Public Opinion in Guangzhou: The Limits of a Popular Approach to Environmental Governance.” *The China Quarterly* 163: 677–704.

Lorentzen, Peter, Pierre Landry, and John Yasuda. 2014. “Undermining Authoritarian Innovation: The Power of China’s Industrial Giants.” *Journal of Politics* 76 (01): 182–194. https://doi.org/10.1017/s0022381613001114.

Ma, Zizhen, Jianguo Deng, Zhen Li, Qing Li, Ping Zhao, Liguo Wang, Yezhu Sun, et al. 2016. “Characteristics of NOx Emission from Chinese Coal-Fired Power Plants Equipped with New Technologies.” *Atmospheric Environment* 131 (x): 164–170. https://doi.org/10.1016/j.atmosenv.2016.02.006.

Manion, Melanie. 2014. “Authoritarian Parochialism: Local Congressional Representation in China.” *China Quarterly* 218 (1): 311–338. https://doi.org/10.1017/S0305741014000319.

McCombs, Maxwell. 2004. *Setting the Agenda: The Mass Media and Public Opinion*. Cambridge: Polity Press.

Mellon, Jonathan. 2013. “Where and When Can We Use Google Trends to Measure Issue Salience?” *Political Science and Politics* 46 (2): 280–290.

Meng, Tianguang, Jennifer Pan, and Ping Yang. 2017. “Conditional Receptivity to Citizen Participation: Evidence From a Survey Experiment in China.” *Comparative Political Studies* 50 (4): 399–433. https://doi.org/10.1177/0010414014556212.

Mertha, Andrew C. 2008. *China’s Water Warriors: Citizen Action and Policy Change*. Ithaca: Cornell University Press.

Mladenka, Kenneth R. 1981. “Citizen Demands and Urban Services: The Distribution of Bureaucratic Response in Chicago and Houston.” *American Journal of Political Science* 25 (4): 693–714.
Oehl, Bianca, Lena Schaffer, and Thomas Bernauer. 2017. “How to Measure Public Demand for Policies When There Is No Appropriate Survey Data?” *Journal of Public Policy* 37 (2): 173–204. https://doi.org/10.1017/S0143814X16000155.
Qiu, Peipei, Hezhong Tian, Chuanyong Zhu, Kaiyun Liu, Jiajia Gao, and Junrui Zhou. 2014. “An Elaborate High Resolution Emission Inventory of Primary Air Pollutants for the Central Plain Urban Agglomeration of China.” *Atmospheric Environment* 86: 93–101. https://doi.org/10.1016/j.atmosenv.2013.11.062.
Schneider, Philipp. 2015. “Validation of Satellite-Derived NO2 Products and Trends Using MAX-DOAS Data: Preparation for Future Copernicus EO Data.” 2. Monitoring Atmospheric Composition and Climate (MACC-III).
Soroka, Stuart, and Christopher Wlezien. 2010. “Degrees of Democracy: Politics, Public Opinion and Policy.” In *Degrees of Democracy: Politics, Public Opinion and Policy*. Cambridge: Cambridge University Press.
Tang, Xiao, Weiwei Chen, and Tian Wu. 2018. “Do Authoritarian Governments Respond to Public Opinion on the Environment? Evidence from China.” *International Journal of Environmental Research and Public Health* 15 (266): 1–15. https://doi.org/10.3390/ijerph15020266.
Truex, Rory. 2016. *Making Autocracy Work: Representation and Responsiveness in Modern China*. Cambridge and New York: Cambridge University Press.
Van Rooij, Benjamin, and Carlos Wing-Hung Lo. 2010. “Fragile Convergence: Understanding Variation in the Enforcement of China’s Industrial Pollution Law.” *Law and Policy* 32 (1): 14–37. https://doi.org/10.1111/j.1467-9930.2009.00309.x.
Vaughan, Liwen, and Yue Chen. 2015. “Data Mining from Web Search Queries: A Comparison of Google Trends and Baidu Index.” *Journal of the Association for Information Science and Technology* 66 (1): 13–22. https://doi.org/10.1002/asi.
Wang, Hua. 2000. “Pollution Charges, Community Pressure, and Abatement Cost of Industrial Pollution in China.” Washington, DC: World Bank. https://openknowledge.worldbank.org/handle/10986/21579.
Wang, Hua, Nlandu Mamingi, Benoit Laplante, and Susmita Dasgupta. 2003. “Incomplete Enforcement of Pollution Regulation: Bargaining Power of Chinese Factories.” *Environmental and Resource Economics* 24 (3): 245–262. https://doi.org/10.1023/A:1022936506398.
Wang, Xie Kang, and Wei Zhen Lu. 2006. “Seasonal Variation of Air Pollution Index: Hong Kong Case Study.” *Chemosphere* 63 (8): 1261–1272. https://doi.org/10.1016/j.chemosphere.2005.10.031.
Wang, Zhan, and Keith Dear. 2017. “Region and Firm Level Determinants of Environmental Regulation Violations: An Empirical Study in Chongqing, China.” *Journal of Cleaner Production* 141: 1011–1022. https://doi.org/10.1016/j.jclepro.2016.09.090.
Wang, Zhen. 2017. “Government Work Reports: Securing State Legitimacy through Institutionalization.” *The China Quarterly* 229 (March 2017): 195–204. https://doi.org/10.1017/S0305741016001521.
Warwick, Mara, and Eonard Ortolano. 2007. “Benefits and Costs of Shanghai ’ s Environmental Citizen Complaints.” *China Information* 21: 237–268.
Wlezien, Christopher. 1995. “The Public as Thermostat: Dynamics of Preferences for Spending.” *American Journal of Political Science* 39 (4): 981. https://doi.org/10.2307/2111666.
———. 2015. “The Myopic Voter? The Economy and US Presidential Elections.” *Electoral Studies* 39: 195–204. https://doi.org/10.1016/j.electstud.2015.03.010.
Wu, Haoyi, Huanxiu Guo, Bing Zhang, and Maoliang Bu. 2017. “Westward Movement of New Polluting Firms in China: Pollution Reduction Mandates and Location Choice.” *Journal of Comparative Economics* 45 (1): 119–138. https://doi.org/10.1016/j.jce.2016.01.001.

Xu, Yong, Jianlin Hu, Qi Ying, Hongke Hao, Dexiang Wang, and Hongliang Zhang. 2017. "Current and Future Emissions of Primary Pollutants from Coal-Fired Power Plants in Shaanxi, China." *Science of the Total Environment* 595: 505–514. https://doi.org/10.1016/j.scitotenv.2017.03.267.

Yu, Xueying. 2014. "Is Environment 'a City Thing' in China? Rural-Urban Differences in Environmental Attitudes." *Journal of Environmental Psychology* 38: 39–48. https://doi.org/10.1016/j.jenvp.2013.12.009.

Zanobetti, Antonella, and Joel Schwartz. 2009. "The Effect of Fine and Coarse Particulate Air Pollution on Mortality: A National Analysis." *Environmental Health Perspectives* 117 (6): 898–903. https://doi.org/10.1289/ehp.0800108.

Zhan, Xueyong, Carlos Wing-Hung Lo, and Shui Yan Tang. 2014. "Contextual Changes and Environmental Policy Implementation: A Longitudinal Study of Street-Level Bureaucrats in Guangzhou, China." *Journal of Public Administration Research and Theory* 24 (4): 1005–1032. https://doi.org/10.1093/jopart/mut004.

Zhang, Jing, and Xiaolan Fu. 2008. "FDI and Environmental Regulations in China." *Journal of the Asia Pacific Economy* 13 (3): 332–353. https://doi.org/10.1080/13547860802131326.

Zheng, Dan, and Minjun Shi. 2017. "Multiple Environmental Policies and Pollution Haven Hypothesis: Evidence from China's Polluting Industries." *Journal of Cleaner Production* 141: 295–304. https://doi.org/10.1016/j.jclepro.2016.09.091.

Zhou, Bangtian, Huizhong Shen, Ye Huang, Wei Li, Han Chen, Yanyan Zhang, Shu Su, et al. 2015. "Daily Variations of Size-Segregated Ambient Particulate Matter in Beijing." *Environmental Pollution* 197: 36–42. https://doi.org/10.1016/j.envpol.2014.11.029.

Zhou, Yi, Shengjun Zhu, and Canfei He. 2017. "How Do Environmental Regulations Affect Industrial Dynamics? Evidence from China's Pollution-Intensive Industries." *Habitat International* 60: 10–18. https://doi.org/10.1016/j.habitatint.2016.12.002.

Zhu, Shengjun, Canfei He, and Ying Liu. 2014. "Going Green or Going Away: Environmental Regulation, Economic Geography and Firms' Strategies in China's Pollution-Intensive Industries." *Geoforum* 55: 53–65. https://doi.org/10.1016/j.geoforum.2014.05.004.